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FACULTAD DE CIENCIAS QUÍMICAS
Departamento de Economía Aplicada I
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**A GENERAL EQUILIBRIUM DEMAND-BASED APPROACH
TO TECHNOLOGICAL CHANGE**

**MEMORIA PARA OPTAR AL GRADO DE DOCTOR
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Javier Santos Arteaga

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José Molero Zayas

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DEMAND-BASED APPROACH TO
TECHNOLOGICAL CHANGE

Doctorando: Francisco Javier Santos Arteaga
Director: José Molero Zayas

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This one is for my family, Debora Di Caprio and Madjid Tavana. Cheers!

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Chapter 1

Introduction

Should the “arrival” of “the” new innovation be dated from its first appearance, or from the time it has gained legitimacy? and: is the legitimation of a new innovation any less fundamental than the act of invention which brings it about? These two questions suggest that the real problem may not be understanding how the process of diffusion unfolds, but understanding how it starts. Geroski (2000, 621)

1.1 On technological demand: the basics

The current thesis deals with and merges three different research lines linked by their respective analyses of the optimal information acquisition processes of rational decision makers. In particular, the information gathering algorithm defined in this thesis relates to the consumer choice literature, the

economic one studying fads and herding phenomena, and the decision theoretical branch of operations research dedicated to study the optimal choice of technology by firm managers.

Consider the problem faced by a rational decision maker regarding what information to gather given a limited capacity to do so. The consumer choice literature studies this problem mainly from a psychological perspective, in particular when dealing with the strategic side of the information transmission process defining the choices made by consumers. In this case, this research line focuses on how the information given to decision makers can be strategically designed to affect their final choice in a way that some predetermined options appear more attractive than others.

Some empirical phenomena identified by this research line include, among many others, the existence of context effects allowing for modifications in the preference formation process of decision makers (Novemsky et al., 2007), guided search mechanisms implemented through screening tools, used, for example, in electronic shopping (Diehl, 2005), and the generation and transmission of superfluous information (Ariely, 2000), with its corresponding additional processing requirements on the decision maker. These effects, together with the limited cognitive ability of decision makers to assimilate information, allow for choice modifications to be induced through their information gathering process.

The previous research line sets the empirical base for the development of the corresponding search theoretical economic models that analyze fads

and herds as rational phenomena, following the seminal works of Banerjee (1992) and Bikhchandani et al. (1992). These models deal with the influence that informative signals have on the optimal (and rational) behavior of the decision makers receiving them. However, studying the influence that information transmission processes, and signals in particular, have on the optimal information gathering behavior and choice structures of decision makers remains outside the main scope of this research line, refer to Chamley (2004) for a comprehensive review of the literature.

In summary, the effect that information transmission processes [signals] have on the choice [strategic] behavior of decision makers within a given equilibrium system has been empirically [formally] analyzed by the consumer choice [economic] research line. The design and study of algorithmic information acquisition processes remains outside their scope but within that of the operations research literature, which, at the same time, tends to overlook the strategic implications that different signaling and preference manipulation strategies have for the information gathering and choice behavior of decision makers.

As a matter of fact, the management/operations research literature has been considering the optimal information gathering problem of firm managers for quite some time, in particular when analyzing the acquisition of a new technology. In this regard, the seminal models of McCardle (1985) and Lippman and McCardle (1991) limited their scope to return functions that were both convex increasing and continuous, a constraint removed by

the most recent research models within this area, such as Ulu and Smith (2009). However, and despite the inclusion of Bayesian learning mechanisms into their algorithms, even the most recent models omit the strategic choice effects inherent to the information transmission process. This research line remains focused on the importance that search costs have in limiting the information processing capacity of generally risk neutral decision makers when deciding whether to continue or stop their search within settings defined by the adoption of a given technology.¹

At the same time, the decision theoretical branch of operations research has recently extended this type of models to allow for comparisons between different technologies. In particular, Paulson Gjerde et al. (2002), as well as Cho and McCardle (2009), emphasize the cumulative and interdependent character of technological evolution. However, while the former authors underline the ability of decision makers to regress to a previous technological state in order to enhance a given product by improving some of its features, the latter ones concentrate on the existence of scale and scope economies

¹For example, Shepherd and Levesque (2002) develop an information gathering algorithm designed to evaluate a business opportunity of unknown profitability. In their model, the decision maker is implicitly endowed with basic memory capacities that allow her to compare the evolution of the expected technological profit between time frames and then use a heuristic decision rule to define the corresponding acceptance and rejection regions. Though their intuition remains valid in our case, it lacks a strategic component in the information transmission process and does not allow for comparisons between competing technologies.

among interdependent technologies and their influence on the adoption of new ones. A more economic related approach is followed by Kornish (2006), who models the influence that network effects via market composition have on the choice of a given technology between two competing ones.

In all these cases, the whole set of technological features is observable and its stochastic evolution defined by a known probability function. Therefore, the strategic effects resulting from signals received regarding the value of unknown technological characteristics as well as those derived from influencing the preferences of decision makers are not analyzed by this branch of the literature.²

Consider a situation where a decision maker is allowed to check a number of characteristics from a set of possible multidimensional choice goods. The search must therefore be at the same time both “between-attributes” and “between-alternatives”. As Bearden and Connolly (2007) summarize, a decision maker must “continuously decide when to stop searching *within* an option - to get a better estimate of its value - and when to stop searching *between* options - to find one of high value. Striking a balance between *depth* (within-option) and *breadth* (between-option) search presents a complex problem.”

²It should be noted that strategic considerations are developed within the game theoretical branch of the operations research literature, refer to the seminal model of Reinganum (1981), that concentrates on the strategic incentives implicit behind the adoption and diffusion of technology but does not deal with the information gathering process affecting technology adoption decisions.

The second and third sections of the thesis formalize and study the optimal information acquisition behavior of a rational decision maker when choosing among multidimensional goods defined by vectors of characteristics. We analyze in detail the case where the decision process is based on the possibility of collecting two pieces of information. This case, commonly considered to be straightforward, is usually overseen by the literature. The evolution of the information acquisition process depends directly on the values of *all the characteristics observed previously*, which prevents the use of dynamic programming techniques in the design of the algorithm. We show that the decision of how to allocate the second available piece of information depends on two well-defined real-valued functions. One function describes the utility that the decision maker expects to derive from continuing acquiring information on the first good, while the other defines the expected utility obtained from starting checking the characteristics of a second good.

In addition, section four extends the information gathering structure defined in the previous sections so as to account for the existence of publicly observable signals within a standard Bayesian learning setting. The introduction of signals within the current multi-dimensional information gathering framework allows for possible generalizations of Banerjee’s (1992) “restaurant” herding model with sequential moves and publicly observable signals to start being considered. Though important differences exist with respect to Banerjee’s model, in particular regarding the quality of the signals received, the introduction of multidimensional goods and a second decision variable al-

allows us to account explicitly for the effects that different risk attitudes, types of signals and learning processes have on the optimal information gathering behavior of decision makers. Signals will be introduced on the second characteristic space in order to intuitively separate the role played by observations from that played by expectations.

These introductory sections provide the basis for the development of a demand-based general equilibrium structure allowing us to analyze the introduction, stability and evolution of technologically superior products through the creation of the niche markets that newcomer firms must monopolize in order to survive.

1.2 Linking demand to supply

The economic concept of quality ladders, Segerstrom et al. (1990) and Grossman and Helpman (1991), has inspired a large literature on industrial evolution mainly developed from the perspective of the supply side, where demand plays a standard representative agent nominal role, see, for example, Grupp and Stadlerb (2005). However, little has been written on the demand incentives to acquire a newly developed technology, with few recent exceptions such as Aversi et al. (1999), Malerba et al. (2003, 2007), Klepper and Malerba (2010) and the papers on the special number to which the latter reference serves as introduction. That is, the neoclassical general equilibrium approach to technological selection and diffusion tends to ignore the explicit

role played by the demand side of the market.³ It has been the [Schumpeterian] evolutionary branch of the theory the one emphasizing, from its very beginnings, the importance of market demand when considering the evolution of technological cycles, see Mowery and Rosenberg (1979).

Demand theoretical models dealing with the acquisition and assimilation of new technology have been mainly developed by the operations research and management literatures.⁴ These research branches concentrate on optimal stopping problems regarding the acquisition of information and implementation of a new technology, see Ulu and Smith (2009) for a recent example. As a result, these disciplines tend to ignore the supply side of the economy, which, while of partial importance from a management perspective, is crucial for economists. Once again, the supply side remains the object of study for neoclassical scholars since Reinganum (1981) opened this line of research for economists. However, the general equilibrium approach required to generate the necessary economic intuition remains an recent evolutionary

³Consider, for example, the model of Tse (2001), who uses the dispersion [heterogeneity] of the demand for quality among consumers to justify the presence of different quality sellers [natural oligopolies] coexisting within a quality ladder industrial structure. Even though his model emphasizes the importance of demand for the technological evolution of an industry, it concentrates on the aggregate [strategic] responses that consumption heterogeneity induces on market suppliers. The same type of supply-biased viewpoint is generally exhibited by the literature on industrial dynamics, see Malerba (2007).

⁴Porter (1990) and the recent literature on global value chains, see Gereffi et al. (2005), constitute an important exception when the demand of firms for industrial and intermediate goods is considered.

phenomenon.

As emphasized by Malerba (2007), a formal analysis of demand and its effects on the development of new technologies, i.e. the incentives of firms to increase their R&D expenditures and innovative efforts, and the structure of a given industry seems to be long overdue. Besides, he argues that such an approach should go beyond the classical industrial organization literature, i.e. Sutton (1998), where demand has a passive role and does not affect the rate of innovation or the direction of technical change.

The current thesis examines the effect that different types of consumers and demand structures may have on the patterns of innovation and industrial dynamics, establishing a explicit link among market demand, firms and technology dynamics. As Malerba (2007) states “... the insertion of demand in the analysis of the relationship between industrial dynamics and innovation is still in its infancy”. Consequently, a formal analysis of demand and its effects on the development of new technologies, i.e. the incentives of firms to increase their R&D expenditures and innovative efforts, and the structure of a given industry seems to be long overdue. Moreover, as emphasized by Malerba (2007), such an approach should go beyond the classical industrial organization literature, i.e. Sutton (1998), where demand has a passive role and does not affect the rate of innovation or the direction of technical change.

Malerba (2007) highlights two key aspects of demand that are relevant for innovation in industries, namely, consumer behavior [including imperfect information with respect to new products and technologies, as well as iner-

tia and habits concerning existing products and technologies] and consumer capabilities [absorptive capabilities and their distribution among consumers and users]. We develop and formally analyze these aspects within a sequential information gathering process that defines the optimal behavior of rational decision makers/consumers when facing different sets of multidimensional goods to choose from.

Four different features of consumer behavior and capabilities will be studied and used to build the formal structure constituting the demand side of the market.

- (i) The existence of imperfect information implies that decision makers will have to gather the required information about the goods offered by a firm before purchasing one. We will define a sequential information gathering algorithm based on the decision maker being able to gather two pieces of information from a set of multidimensional goods. This limit is imposed to account for existing information processing costs, either pecuniary or cognitive, and to allow for a simple numerical analysis illustrating the theoretical results obtained.⁵ The preferences and absorptive capabilities of decision makers will be shown to determine

⁵In addition, the literature usually concentrates on a small number of attributes when describing the products available to consumers, i.e. performance and cheapness in the case of Malerba et al. (2003, 2007) and variety and quality in the case of Bohlmann et al. (2002). Bearden and Connolly (2007) survey the literature on multidimensional consumer choice, while Gaines (2003) provides a review at the organizational level.

their willingness to continue searching within a given market for better expected products. In particular, we will illustrate numerically how the willingness to search of decision makers depends on their degree of risk aversion and how it is influenced by the reception of signals defined on the distribution of unobserved characteristics.⁶

Moreover, the presence of habits and consumption inertia, i.e. the ability of firms to build [educate] a consumer base expecting a minimum quality level among the goods it offers to be guaranteed, will be shown to determine the continuity of the expected utilities derived from a given search and generate different reversible information gathering continuation areas when searching within a market.

- (ii) The introduction of technologically superior products may be signaled by firms. It will be assumed that only those decision makers who are sufficiently experimental will update their beliefs and demand thresholds when gathering information and choosing a product from a firm.

Experimental decision makers are defined by Malerba et al. (2003,

⁶In a related theoretical scenario, Vergari (2005) investigates how the economic environment, i.e. government preferences, affects the efficiency of technology choice in a setting where firms choose sequentially between a safe old technology and a risky new one. Vergari (2005) incorporates government preferences in the form of a noisy public signal to the information externalities that define standard herding environments in order to obtain a smaller bias against the adoption of new and superior technologies. In our model, it is indeed the credibility of the noiseless signals observed what induces stricter acceptance criteria on the set of technologically superior products among decision makers.

2007) as those who crave new technologies in existing products or look for completely new products in new demand segments. We will refer to this type of consumers as perfect foresight ones, while myopic decision makers, on the other hand, will be those whose behavior remains unaffected by the signals of firms.

(iii) Inertia and habits with respect to existing products and technologies will determine the ability of decision makers to shift their information gathering processes between different product markets. In the words of Malerba et al. (2003), “customers are very sophisticated and won’t buy a new model computer unless it is as good as or better than the old model ones” (pg. 8). Hence, the incentives for a decision maker to shift between different product markets must depend on whether or not the technological development introduced allows her to improve upon the existing product characteristics.

(iv) The preferences and absorptive capabilities of decision makers will determine their willingness to continue searching within a given market for better expected products. In this sense, we will illustrate numerically how risk neutral decision makers are less averse to search among the goods within a given market than risk averse ones.

The multiple characteristics approach that we follow is not only typical of the consumer choice literature, see Bearden and Connolly (2007), but has also been employed to measure technological evolution in the economic

one, see Saviotti (1982), Alexander and Mitchell (1984), and Saviotti and Metcalfe (1984). These authors based their empirical approaches on sets of characteristics describing the technology implicit in a given product and tried to develop indicators to measure the effects of technological innovation and change, i.e. sophistication, on the characteristics and valuation of the product. The main problem faced by these authors was to consider the relative weights of the characteristics when defining the product. As Saviotti points out in the abstract of his (1982) paper, “These indicators can be applied only to multicharacteristic products with easily quantifiable characteristics. However, products that satisfy these requirements account for a very large share of the market for industrial goods.”

These ideas, based on the demand analysis of Lancaster (1966), will be formally applied here to define the information gathering process of rational decision makers. Note, however, that we are not implying that two characteristics, or two classes of them, suffice to account for the complex nature of the technology inherent to a product. Indeed, trying to do so would miss most of the technological changes incorporated within a given product, see Alexander and Mitchell (1984). However, despite the apparent simplicity of the decision algorithm, the resulting choice environment [defined by decision makers] will be far from trivial and allow for the design of a demand structure that accounts for signaling and learning phenomena while being based on relatively straightforward technical assumptions.

We are aware of the behavioral limitations displayed by the branch of

decision theory based on expected utility maximization, under risk or uncertainty, and the lack of empirical validity exhibited by the main axioms of expected utility, see Di Caprio and Santos-Arteaga (forthcoming). However, we will model the behavior of decision makers using these axioms and the corresponding economic intuition, while trying to accommodate the main behavioral properties highlighted by Aversi et al. (1999), by considering the simplest non-trivial information gathering and choice environment that may be faced by a decision maker. That is, we aim at smoothing the frontier between the behavioral endogenous preference approach of Aversi et al. (1999) and the decision theoretical setting on which this thesis is based. In order to do so we abstract from context, temporal and social effects both in the order of the characteristics and the shape of the utility function, see Aversi et al. (1999: 356).⁷

Our information gathering process leads an almost lexicographic choice structure to emerge from a set of continuous preference relations defined on multi-dimensional objects.⁸ This type of choice pattern is in accordance with the properties of consumption described by Aversi et al. (1999: 365), who state that “micro-consumption patterns are likely to be characterized by

⁷Note, however, that these effects could be assumed to shape or directly determine the order defined by the decision makers both within and among characteristics.

⁸Formally, this type of behavior does not constitute a problem since lexicographic choices can be shown to follow from continuous preferences and to be representable by continuous utility functions in environments with incomplete information as the current one, see Di Caprio et al. (2010).

roughly lexicographic patterns of consumers selection over hedonic attributes and goods.”

In an intuitively related setting, Tripsas (2001) argues that it is a discontinuous change in the preferences of decision makers what usually drives the adoption of new technology in an industry. Our analysis of demand will also exhibit discontinuities in the choice process of decision makers emerging as a result of changes in technological evolution. Moreover, in our setting it is the receptivity of decision makers to a credible signal, a common approach in the economic literature on herding phenomena, what drives this discontinuous (though emerging from continuous preferences) behavior.

Even though the choices made by decision makers will determine the survival of some products and technologies but not others, we will not provide them with the required sophistication so as to become users in the sense of Von Hippel (1988) and Rogers (2003), where product users are able to interact with suppliers to develop and improve the goods that are initially consumed.⁹

⁹When considering consumer behavior and modeling how consumers decide whether or nor to accept an innovation and how this decision affects its diffusion, the literature generally shifts towards a marketing approach, which tends to concentrate on the process of diffusion, see Mahajan, Muller, and Bass (1990). For a survey of the literature on the diffusion of process technologies see Baptista (1999), who emphasizes the existing similarities between the diffusion of industrial processes and that of new consumer durables. Note, however, that if the dynamics of technological innovation are interpreted in the way proposed by Abernathy and Utterback (1975), there may exist important differences

That is, our model is not so ambitious so as to account for a demand-based generation of new technological paradigms, a possibility illustrated by van den Erde and Dolfsma (2005), or of completely new markets, see Geroski (2000).¹⁰ The question we try to answer initially is a simpler one: if a new technologically superior (set of) product(s) becomes available, as is required for the development of a new market, see Abernathy and Utterback (1978), and its existence could be credible signaled by firms, would they do so based on the expected reaction of consumers?

Thus, we are more interested in the microeconomic properties of the choice process between products with different levels of technological development faced by decisions makers than in the dynamic trend of the technological process itself, an approach followed by the stochastic learning structures of Stoneman (1981), Aversi et al. (1999), Fatas-Villafranca and Saura-Bacaicoa between the initial phases of technological emergence, before a dominant design arises, and the following ones based on an established (dominant) design. De facto, product innovation is much more important in the initial phases while process innovation gains relevance afterwards, as the (surviving) incumbent firms exploit the corresponding scale and scope economies. This type of evolutionary pattern has also been emphasized by Pavitt (1984) and Malerba and Orsenigo (1997). Brown and Greenstein (2000) identified econometrically the lead users that helped creating niche markets for new technological products within the computer industry using data on the demand for speed and memory [two main characteristics] of mainframe computers during the second half of the eighties.

¹⁰In the latter case, a set of psychology and cognitive science micro-foundations for market generation by expert entrepreneurs is presented by Dew et al. (2011) as a critic to the standard rational decision theoretical approach.

(2004), and Malerba et al. (2007).¹¹ That is, following Geroski (2000), we will concentrate our efforts in analyzing the technological transition behavior of decision makers at the most basic microeconomic level instead of considering the dynamic [diffusion] trend of the process.

In this regard, three different formal settings will be considered through Sections 4 to 7, respectively, each analyzed both theoretically and numerically.

The first setting [described in Section 4] illustrates the idea of performance thresholds described by Adner and Levinthal (2001). Decision thresholds arise naturally within our theoretical environment and allow us to analyze how consumer preferences affect the emergence of disruptive technologies, which, in our case, have already been developed but must be introduced in the market, see Adner (2002). Indeed, a superior distribution of [desirable] variants of the product characteristics will be generated, as is required for the development of a new market, see Abernathy and Utterback (1978). We show how the willingness to search of decision makers depends on their de-

¹¹These papers consider the evolution of technology adoption as a stochastic process defined within a [diffusion] difference/differential (depending on the paper) equation, allowing for a macroeconomic approach to the study of technology diffusion. Stoneman (1981) accounts for the ability of decision makers to learn in a Bayesian manner and incorporates the corresponding stochastic process to the design of diffusion patterns. Aversi et al. (1999), Fatas-Villafranca and Saura-Bacaicoa (2004), and Malerba et al. (2007) provide sophisticated computable versions based on the intuitive history-friendly behavioral micro-foundations of demand.

gree of risk aversion, a result already developed by Di Caprio and Santos Arteaga (2009), and how it is influenced by the reception of signals defined on the distribution of unobserved characteristics. In doing so, we reach the same type of conclusion as Jensen (1988), Cho and McCardle (2009), and Ulu and Smith (2009) regarding the effect that first order stochastic dominance improvements on expected revenue/utility have on the incentives of decision makers to adopt a new technology. That is, signaling the development of a more advanced technology does not necessarily lead to faster adoption. We illustrate how a positive *credible* signal on the development of a technology, or a choice good, leads to stricter continuation criteria in terms of the characteristic threshold value required to be observed in order to accept the more advanced technology. Applications to knowledge management and decision support systems follow immediately from the specified framework.

The intuition giving place to the second setting [described in Section 5] follows from Christensen and Rosenbloom (1995, 238) and relates directly to their analysis of nested hierarchies and value networks

“The viewpoint that differences in firms’ market positions drive differences in how they assess the economics of alternative technological investments is rooted in the notion that products are systems comprised of components which relate to each other in a designed architecture [...] Furthermore, the end-product may also be viewed as a component within a system-of-use, relating to other components within an architecture defined by the user. In

other words, products which at one level can be viewed as complex architected systems act as components in systems at a higher level.”

In particular, when evaluating the product attributes considered to be central for the network the list of characteristics reduces to two or three per product, see Christensen and Rosenbloom (1995, 239). Specifically, Christensen and Rosenbloom (1995, 240) state that associated with each network is a unique rank-ordering of the importance of various performance attributes, whose rank-ordering differs from that employed in other value networks. In this sense, our decision makers will [subjectively] account for the expected relative performance of their most preferred attributes when determining their information gathering incentives.

The third and final decision theoretical setting [described in Section 6] relates to the classical representation of technological competition described by Foster (1986) and restated by Adner and Snow (2010), which focuses on the ability of old technology incumbents to recognize plausible threats and manage the adoption of the new technology on time.¹² We will therefore be considering our decision theoretical structure from a supply side perspective, since, after all, it is firm’s managers who decide whether or not to introduce (adopt) a technologically superior product in (from) the market. We will also indirectly account for the remarks made by Geroski (2000) when referring to

¹²Antonelli (1993) illustrates the pervasive effects derived from being locked-in into a large base of the [old] inferior technology so that high costs from switching to the [new] superior one are faced.

the creation of a new market and the fuzziness involved in the demand of decision makers for the corresponding innovation due to their little practical knowledge or experience of the innovation itself.

The assumed generality of the decision theoretical model presented allows for our decision makers to be interpreted as either firm managers or consumers, depending on the degree of sophistication imposed on them. For example, as emphasized by Adner and Snow (2010), the innovation literature has long recognized that technology presents incumbent firms with a set of challenges triggered by *technology induced discontinuities*. The effectiveness of the incumbent reactions to technological discontinuous threats depends on a host of factors that contribute to the long term viability of firms, ranging from the perception of threats and the subtlety of the change to the impact on the competences and dominant customers of the firm, see Adner and Snow (2010) for a review of the literature on this topic.

On the other hand, Tripsas (2001) argues that the timing of transition between different technology generations is determined as much by the evolution of the demand-side user preferences, in particular, *preference discontinuities*, as by the evolution of technology, and provides empirical evidence from the typesetter industry to illustrate her point.¹³ This evidence constitutes a direct criticism of the technology life cycle literature, where it is implicitly assumed that preferences evolve with technology but do not shape it,

¹³Tripsas (2001) relies on either new preferences or discontinuities in the current preferences of consumers to account for the adoption of a new technology within an industry.

as they remain constant while technological progress evolves within a given trajectory.

We will show in Section 7 that discontinuous technology demand patterns do not necessarily emerge from preference discontinuities. Indeed, perfectly rational and continuous preferences may give place to discontinuous behavioral patterns in the information gathering [and choice] process[es] of decision makers.

Our basic initial approach to the information gathering process of decision makers imposes habits and consumption inertia implicitly, leading decision makers to expect a minimum quality level or *certainty equivalent* good to be guaranteed from a random purchase. However, a more complex decision theoretical structure results if habits and consumption inertia are excluded from the information gathering process of decision makers and it is assumed that decision makers do not purchase a good unless its observed characteristics deliver a higher expected utility than those of the reference certainty equivalent good.

The intuition for the latter approach follows from the previously cited work of Christensen and Rosenbloom (1995) on nested hierarchies and value networks. These authors consider products as systems comprised of components which relate to each other in a designed architecture. Specifically, as emphasized before, Christensen and Rosenbloom (1995) state that associated with each network is a unique rank-ordering of the importance of various performance attributes that differs from those orderings employed in other value

networks. However, despite the complex structure of the value networks defined by these authors, when evaluating the product attributes considered as central to the network the list reduces to two or three characteristics per product.

In this regard, it could be assumed that the ability of a firm to credibly guarantee decision makers a given [quality level] certainty equivalent good depends on its position within a given network architecture or hierarchic system.¹⁴ Therefore, a well established incumbent should have a clear advantage over an unknown newcomer when guaranteeing a certainty equivalent good to potential consumers. We will indeed illustrate in Section 7 how being unable to guarantee a minimum certainty equivalent good decreases significantly the ability of firms to introduce their products in a given market. This will be the case even if they signal the existence of technologically superior products and despite the credibility of the signal issued. These results help emphasizing the importance that consumer education, habits and inertia have in smoothing the behavior of decision makers when considering the acquisition

¹⁴This assumption is similar to the money back guaranteed one generally imposed in the industrial organization literature, see Nizovtsev and Novshek (2004) for a review of the literature on this topic. Nizovtsev and Novshek (2004) also illustrate how money back guarantees may constitute an optimal experimentation strategy among firms in markets for experience goods with repeated purchases. In this regard, the results obtained in the current thesis could be easily extended to complement those of Nizovtsev and Novshek (2004), since the second unobserved characteristic defining the information gathering algorithm behaves as an experience component of the good under consideration.

of products within different technologically developed markets.

1.3 Technological transition

Sections 9 and 10 present a basic formal model of decision making and choice under risk where the transition process between goods with different levels of technological sophistication takes place absent improvements in the old technology, consumption inertia and any other possible market friction, as those integrated by De Lisoa and Filatrellab (2011) in their memory effect variable.¹⁵

We will illustrate how, even without market frictions, the initial rejection probability assigned by rational well informed decision makers to a newly introduced technologically superior set of goods increases. As a result, the worst available version of a new technologically superior product will be used to generate the corresponding signal-induced monopolistic market, since any improved version would lead to lower expected revenues for the signaling firm. This will be the case despite the fact that an improved distribution of variants of one of the main characteristics composing the goods is generated and *credibly* signaled by firms. In this sense, the basic transition model merges the main ideas from the economic literature on signaling and rational

¹⁵Similar frictions were considered by Geroski (2000) when referring to the creation of a new market and the fuzziness involved in the demand of agents for the innovation, due to their little practical knowledge or experience of the innovation being introduced.

herds, see Chamley (2004), with the behavioral approach to technological demand developed by Malerba et al. (2007).¹⁶

As stated in the previous subsection, our empirical counterpart would be given by Brown and Greenstein (2000), who, using the demand for speed and memory (two main characteristics) of mainframe computers during the second half of the eighties, identified econometrically the set of lead users that generated the technological niche markets for the new computer products. Indeed, the motivation for their paper followed from the fact that despite the decline in quality adjusted price during the period of analysis, consumers did not make the corresponding shift from small computer systems to larger ones.¹⁷

Furthermore, while the existing delays in innovation acquisition and diffusion have been widely documented by the economic literature, Geroski (2000), and formally analyzed by the operations research one, the strate-

¹⁶It should be noted that the importance of knowledge and learning as crucial economic forces when dealing with innovation and economic transformation processes was already emphasized by Lundvall and Johnson in 1994. However, these forces have been mainly analyzed from the supply side of the economy, where their vital role for technological development and economic growth has been repeatedly stated, see Lundvall and Borrás (1997) and Lundvall (2004). See also Lundvall (1988) for an exception to this trend, where user-producer interactions are accounted for as a main determinant of innovation processes.

¹⁷Besides, adding to the similarity with our technological transition environment, their product space was assumed continuous due to the large number (variety) of memory and speed characteristics that could be chosen by consumers.

gic incentives of firms to introduce technologically superior products remain oblivious to the decision patterns defining the demand side of the (market) system, see Beath et al. (1995). The technological transition sections introduce a strategic *general equilibrium* approach to the process of technological diffusion. It will be shown how the stricter signal-induced continuation criteria that delay the adoption of technologically superior goods (by the demand side) would also constraint their introduction (by the supply side) unless sufficiently high monopolistic rents are guaranteed to the signaling firm. However, even if this were the case, technological improvements would not necessarily lead to higher expected revenues for the firms introducing them.

These sections provide the starting point and basic intuition required for the development of the general equilibrium structure studied through the remaining of the thesis.

1.4 On technological supply: the basics

Given the demand determinants described in the previous subsections, firms will have to decide strategically whether or not to signal the introduction of a technologically superior good. As a result, the optimal and rational choices made by decision makers will be determined by their degree of risk aversion, their receptiveness and assimilation of signals, their ability to shift choices between markets *and the signaling decisions made by firms*.

The supply side of the economy will be modeled through a three time periods duopoly where two types of signaling equilibria, based on the assumed information transmission structure, will be considered. A standard Nash equilibrium scenario will be used to force firms to commit to their initial period signaling strategy while a subgame perfect equilibrium will allow them to retrieve interim observations regarding the signaling strategies of their rivals and act accordingly. The latter type of equilibrium is defined to allow for habits and consumption inertia in the information gathering process of decision makers and to illustrate how the coordinated creation of niche markets, where newly introduced technologically superior products may initially survive, takes place.¹⁸ In other words, we will identify the conditions required for technological niche markets to emerge and relate them to the type of equilibrium and the properties of demand under consideration.

In Section 11, we formalize the intuitive argument presented by Malerba et al. (2003, 2007), who state that the successful introduction of a radically

¹⁸Rahman and Loulou (2001) consider both types of equilibria in an intuitively related environment, where they model a firm's technology adoption decisions in a duopoly. These authors justify the Nash pre-commitment equilibrium as relevant for technologies that take a long time to acquire and install, while subgame perfection would be relevant when technologies can be acquired and installed quickly and the rival's decisions are observable right after they are made. We allow for habits and consumption inertia in order to account for the fact that the existence of a technologically superior set of goods does not imply an immediate transition to the market defined by the newly introduced technology, see, for example, Geroski (2000) and the literature cited within it.

new technology in an industry, with a dominant design and a small collection of dominant firms that have emerged using the older technology, may be dependent on the presence of a group of experimental customers, on diverse preferences and needs among potential users, or on them both.¹⁹ However, while Malerba et al. (2003, 2007) simulate a behavioral evolutionary general equilibrium model of the firm, we follow a game theoretical approach based on the rational choices made by decision makers when gathering information on the sets of goods offered by firms.²⁰

It should be noted that we are aware of the reliance placed on the papers of Malerba (2007) and Malerba et al. (2003, 2007). This has been done due to the fact that, as already stated in the introductory section, the demand approach to technology adoption is usually undertaken from an operational research perspective, which concentrates more on the optimal stopping properties of the corresponding decision algorithms than on the resulting consequences for economic equilibria, a particularly relevant approach

¹⁹Indeed, if all decision makers are myopic, and in accordance with the conclusions reached by Malerba et al. (2003, 2007), new firms signaling the existence of a technologically superior product would be unable to stay around long enough so as to become viable.

²⁰Malerba et al. (2003, 2007) justify their reluctance to follow a game theoretical approach due to the various types of limitations that these models impose formally, ranging from cognitive biases to organizational factors. We aim at illustrating that a rational [decision theoretical] demand environment coupled with a game theoretical supply setting may indeed lead to their same conclusions.

when studying this phenomenon from a strategic point of view. The operational research and management theoretical literature on the demand for new technology can be classified as game theoretic, a research line started by Reinganum (1981), or decision theoretic, following Jensen (1982). Both approaches were initially developed within the economic literature but taken over by the management/operational research one, leading to two separate and clearly differentiated streams of research. Decision theoretical models defining demand are based on stopping criteria determining the introduction or dismissal of a new technology, refer to the seminal papers of Jensen (1982) and McCardle (1985). On the other hand, game theoretical models are mainly concerned with the diffusion of technology, see Beath et al. (1995). Hence, the lack of interaction, at a formal level, between the strategic diffusion of technology by firms and its demand creation by consumers is a problem that the general equilibrium approach so commonly used in economics should help solving.

We illustrate how, in accordance with the results of Ireland and Stoneman (1986), perfect foresight [regarding expected rapid technological change] causes a slow-down in the adoption of the currently available [unsigned] technology relative to myopia. That is, the introduction of a technologically superior set of goods may not lead to its immediate acquisition by consumers. This will be the case despite the fact that, when purchasing a good, if any, the basic reference characteristics considered by decision makers will be assumed to be given by the certainty equivalent values delivered by the set of

goods defined within the current unsigned market. This assumption keeps the section in line with the intuition behind the quality ladder literature, where technological improvements are defined with respect to the currently available version of the good.

Given the properties defining the demand side of the market and the type of decision makers composing it, we present a game theoretical analysis of a duopoly facing the strategic decision of whether or not to signal the existence of a technologically superior good. The set of equilibria obtained are used to determine the dynamic behavior of the industry. In particular, the model highlights the importance that stable monopolistic technological rents and perfect foresight decision makers have for the generation of technological niche markets where firms signaling the existence of a technologically superior good may survive.

Section 12 shows how, given the set of natural constraints and assumptions introduced to define the behavior of both decision makers and firms, the generation of technological niche markets may also depend on the ability of decision makers to reverse their information gathering processes and compare the goods observed in both markets before making a choice. In particular, decision reversibility is necessary, but not sufficient, for the emergence of technological niche markets. The credibility of the signals observed and the subsequent Bayesian updates of the information gathering processes prevent us from requiring the existence of consumers with large preferences for experimentation, as Malerba et al. (2003, 2007) do, for the creation of

niche markets to take place.

Finally, it is known that the Arrow effect provides a theoretical justification for the dynamic behavior of industries where incumbent firms have a lower pecuniary incentive than newcomers to develop and introduce technological improvements over the currently existing set of products. However, the Arrow effect is unsuited to explain recent empirical phenomena such as vintage effects, see , or the retreat strategy of firms described by Adner and Snow (2010). We illustrate how the decision of not signaling the existence of a technologically superior set of goods may arise as an optimal subgame perfect equilibrium within the demand based environment defined in the section. That is, we obtain subgame perfect equilibria where the introduction of technologically superior products and subsequent generation of niche markets, i.e. climbing the technological quality ladder, is suboptimal for the signaling firm.

Chapter 2

Demand

2.1 Basic notations and main assumptions

Given the range of influences and applications defined in the previous introductory section, the thesis may be considered under the scope of any of the described research lines. However, we will bias our notation towards the consumer choice and economic sides and express the search algorithm in utility terms. This notational choice is made to differentiate our model from the value functional forms required by the dynamic programming and operations research literature. Due to formal reasons that will become evident below, the current demand model cannot be defined in the standard dynamic programming terms commonly considered within this branch of the literature.

That is, the demand algorithm described through the thesis must be

redefined after each observation is gathered by the decision maker and recalculated in terms of *all previously observed variables, their sets of possible combinations and corresponding expected payoffs*, which prevents the use of standard dynamic programming techniques applied by the operations research literature. This requisite is justified by the low dimensionality of the model and the memory capacity with which decision makers are endowed when comparing goods in basic information evaluation scenarios. While such an assumption may become prohibitive in larger dimensional settings, it is imposed here to account for the satisficing capacity constraints defined by Simon (1997) within a fully rational environment.

Let X be a nonempty set and \succsim a *preference relation* defined on X . A *utility function representing a preference relation \succsim on X* is a function $u : X \rightarrow \mathbb{R}$ such that:

$$\forall x, y \in X, \quad x \succsim y \Leftrightarrow u(x) \geq u(y).$$

The symbol \geq denotes the standard partial order on the reals. When $X \subseteq \mathbb{R}$ and \succsim coincides with \geq , we say that u is a *utility function on X* .

Let \mathcal{G} denote the set of all goods and fix $n \in \mathbb{N}$. For every $i \leq n$, let X_i represent the set of all possible variants for the i -th characteristic of any good in \mathcal{G} and X stand for the Cartesian product $\prod_{i \leq n} X_i$. Thus, every good in \mathcal{G} is described by an n -tuple $\langle x_1, \dots, x_n \rangle$ in X . X_i is called the *i -th characteristic factor space*, while X stands for the *characteristic space*.

Following the classical approach to information demand by economic

agents, see Wilde (1980), we restrict our attention to the case where each X_i is identified with a compact and connected non-degenerate real subinterval of $[0, +\infty)$. The topology and the preference relation on each X_i are those induced by the standard Euclidean topology and the standard linear order $>$, respectively.

Without loss of generality, we work under the following assumptions.

Assumption 1. For every $i \leq n$, there exist $x_i^m, x_i^M > 0$, with $x_i^m \neq x_i^M$, such that $X_i = [x_i^m, x_i^M]$, where x_i^m and x_i^M are the minimum and maximum of X_i .

Assumption 2. The characteristic space X is endowed with the product topology τ_p and a strict preference relation \succ .

Assumption 3. There exist a continuous additive utility function u representing \succ on X such that each one of its components $u_i : X_i \rightarrow \mathbb{R}$, where $i \leq n$, is a continuous utility function on X_i .¹

Assumption 4. For every $i \leq n$, $\mu_i : X_i \rightarrow [0, 1]$ is a continuous probability density on X_i , whose support, the set $\{x_i \in X_i : \mu_i(x_i) \neq 0\}$, will be denoted by $\text{supp}(\mu_i)$.²

¹Let \succsim be a preference relation on $\prod_{i \leq n} X_i$. A utility function $u : \prod_{i \leq n} X_i \rightarrow \mathbb{R}$ representing \succsim on $\prod_{i \leq n} X_i$ is called *additive* (Wakker, 1989) if there exist $u_i : X_i \rightarrow \mathbb{R}$, where $i \leq n$, such that $\forall \langle x_1, \dots, x_n \rangle \in \prod_{i \leq n} X_i$, $u(\langle x_1, \dots, x_n \rangle) = u_1(x_1) + \dots + u_n(x_n)$.

²The results introduced through the thesis are derived for continuous μ_1 and μ_2 probability densities. The remaining cases, quite similar to the continuous one, are left to the reader.

The probability densities μ_1, \dots, μ_n must be interpreted as the subjective “beliefs” of the decision maker. For $i \leq n$, $\mu_i(Y_i)$ is the subjective probability that a randomly observed good from \mathcal{G} displays an element $x_i \in Y_i \subseteq X_i$ as its i -th characteristic.³

Following the standard economic theory of choice under uncertainty, we assume that the decision maker elicits the i -th certainty equivalent value induced by the subjective probability density μ_i and the utility function u_i as the reference point against which to compare the information collected on the i -th characteristic of a certain good.

Given $i \leq n$, the *certainty equivalent of μ_i and u_i* , denoted by ce_i , is a characteristic in X_i that the decision maker is indifferent to accept in place of the expected one to be obtained through μ_i and u_i . That is, for every $i \leq n$, $ce_i = u_i^{-1}(E_i)$, where E_i denotes the expected value of u_i . The existence and uniqueness of the i -th certainty equivalent value ce_i are guaranteed by the continuity and strict increasingness of u_i , respectively.

2.2 Expected search utilities

The set of all goods, \mathcal{G} , is identified with a compact and convex subset of the n -dimensional real space \mathbb{R}^n . In the simplest non-trivial scenario, \mathcal{G} consists

³The probability densities μ_1, \dots, μ_n are assumed to be independent. However, the algorithm allows for subjective correlations to be defined among different characteristic within a given good.

of at least two goods and the decision maker is allowed to collect two pieces of information, not necessarily from the same good. That is, once the value of the first characteristic from one of the goods becomes known to the decision maker, she has to decide whether to check the second characteristic from the same good, or to check the first characteristic from a different good. Henceforth, we denote by J and K the two goods that can be randomly checked by the decision maker.

We show below that the decision of how to allocate the second available piece of information depends on two real-valued functions defined on X_1 . The decision maker considers the sum $E_1 + E_2$, corresponding to the expected utility values of the pairs $\langle u_1, \mu_1 \rangle$ and $\langle u_2, \mu_2 \rangle$, as the main reference value when calculating both these functions.

Assume that the decision maker has already checked the first characteristic from good J and that she uses her remaining information piece to observe the second characteristic from J . In this case, the expected utility gain over $E_1 + E_2$ varies with the value x_1 observed for the first characteristic. For every $x_1 \in X_1$, let

$$P^+(x_1) = \{x_2 \in X_2 \cap \text{supp}(\mu_2) : u_2(x_2) > E_1 + E_2 - u_1(x_1)\}$$

and

$$P^-(x_1) = \{x_2 \in X_2 \cap \text{supp}(\mu_2) : u_2(x_2) \leq E_1 + E_2 - u_1(x_1)\}.$$

$P^+(x_1)$ and $P^-(x_1)$ define the set of values for the second x_2 characteristic

from good J such that their combination with the observed first x_1 characteristic delivers a respectively higher or lower-equal utility than a randomly chosen good from \mathcal{G} .

Let $F : X_1 \rightarrow \mathbb{R}$ be defined by:

$$F(x_1) \stackrel{def}{=} \int_{P^+(x_1)} \mu_2(x_2)(u_1(x_1) + u_2(x_2))dx_2 + \int_{P^-(x_1)} \mu_2(x_2)(E_1 + E_2)dx_2$$

$F(x_1)$ describes the decision maker's expected utility derived from checking the second characteristic x_2 of good J after observing that the value of the first characteristic is given by x_1 . Note that, if $u_2(x_2) + u_1(x_1) \leq E_1 + E_2$, then choosing a good from \mathcal{G} randomly delivers an expected utility of $E_1 + E_2$ to the decision maker, which is higher than the expected utility obtained from choosing good J , that is, $u_2(x_2) + u_1(x_1)$.

Note, however, that despite the formal postulates of expected utility theory, rational decision makers are not obliged to choose randomly from the set of available goods. That is, despite their expectations, decision makers are aware of the fact that the certainty equivalent good is not guaranteed as the result of a random choice. Indeed, it seems plausible to assume that if the information gathering (search) process does not provide decision makers with a good whose expected utility is higher than $E_1 + E_2$, then they refrain from making a random purchase from the set of available goods. If this were the case, the expected search utilities defined above should be modified to account for the respective changes in the expected utilities derived from the corresponding search processes.

In order to simplify the presentation we will refer to the case defined above as the guaranteed certainty equivalent scenario (g.c.e.s.), where decision makers decide to choose randomly within the set of available goods if the search process does not deliver a good whose expected utility is higher than the one provided by the certainty equivalent good. However, decision makers may also refrain from making a random purchase, a case which will be referred to as the refused certainty equivalent scenario (r.c.e.s.).

The $F(x_1)$ function defined by decision makers within the r.c.e.s. simplifies to

$$F(x_1|rf) \stackrel{def}{=} \int_{P^+(x_1)} \mu_2(x_2)(u_1(x_1) + u_2(x_2))dx_2,$$

where the $P^+(x_1)$ set is identical to the one defined within the g.c.e.s. Indeed, $F(x_1|rf)$ is simply $F(x_1)$ without the second right hand side expression.

Consider now the expected utility that the decision maker could gain over $E_1 + E_2$ if the second available piece of information is employed to observe the first characteristic from good K . For every $x_1 \in X_1$, let

$$Q^+(x_1) = \{y_1 \in X_1 \cap \text{supp}(\mu_1) : u_1(y_1) > \max\{u_1(x_1), E_1\}\}$$

and

$$Q^-(x_1) = \{y_1 \in X_1 \cap \text{supp}(\mu_1) : u_1(y_1) \leq \max\{u_1(x_1), E_1\}\}.$$

$Q^+(x_1)$ and $Q^-(x_1)$ define the set of values for the first y_1 characteristic from good K such that they deliver a respectively higher or lower-equal utility

than the maximum between the observed first x_1 characteristic from good J and a randomly chosen good from \mathcal{G} .

Define $H : X_1 \rightarrow \mathbb{R}$ as follows:

$$H(x_1) \stackrel{def}{=} \int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_2) dy_1 + \int_{Q^-(x_1)} \mu_1(y_1)(\max\{u_1(x_1), E_1\} + E_2) dy_1.$$

$H(x_1)$ describes the expected utility obtained from checking the first characteristic y_1 of good K after having already observed the value of the first characteristic x_1 from good J . If $u_1(y_1) \leq \max\{u_1(x_1), E_1\}$, then the decision maker must choose between J and a randomly chosen good from \mathcal{G} , delivering an expected utility of E_1 .

The corresponding $H : X_1 \rightarrow \mathbb{R}$ function defined by decision makers within the r.c.e.s. is given by

$$H(x_1|rf) \stackrel{def}{=} \int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_2) dy_1 + \int_{Q^-(x_1|rf)} \mu_1(y_1)(u_1(x_1) + E_2) dy_1,$$

with

$$Q^+(x_1) = \{y_1 \in X_1 \cap \text{supp}(\mu_1) : u_1(y_1) > \max\{u_1(x_1), E_1\}\}$$

and

$$Q^-(x_1|rf) = \{y_1 \in X_1 \cap \text{supp}(\mu_1) : u_1(y_1) \leq \max\{u_1(x_1), E_1\} \wedge x_1 \geq ce_1\}.$$

The second right hand side term of $H(x_1|rf)$ together with $Q^-(x_1|rf)$ illustrate the main differences with respect to the g.c.e.s. Decision makers will only purchase a good and account for the corresponding expected utility

if $x_1 \geq ce_1$. That is, the expected utility derived from X_1 realizations below the certainty equivalent value equals zero.

Finally, note that the domain of all the F and H functions is the support of μ_1 .

Pointwise comparisons between the functions cannot be undertaken analytically due to the variety of possible domains and functional forms that may define their behavior. However, for a given set of probability densities and utilities, changes in the curvature of the $F(x_1)$ and $H(x_1)$ functions (degree of risk aversion) and their effect on the optimal information gathering behavior of decision makers can be analyzed numerically, see Di Caprio and Santos Arteaga (2009). In the current thesis, we will also illustrate numerically how changes in the degree of risk aversion of decision makers affect their optimal information gathering behavior within a r.c.e.s. It should be already emphasized that the resulting $F(x_1|rf)$ and $H(x_1|rf)$ functions describe a more complex choice environment than $F(x_1)$ and $H(x_1)$, due mainly to the discontinuities generated by $H(x_1|rf)$.

Chapter 3

The functions $H(x_1)$ and $F(x_1)$

The function $H(x_1)$ is always constant on the interval $[x_1^m, ce_1]$ and its value is always above the sum of the expected values of u_1 and u_2 . That is, for every $x_1 \leq ce_1$,

$$H(x_1) = \int_{ce_1}^{x_1^M} \mu_1(y_1)u_1(y_1)dy_1 + E_1 \int_{x_1^m}^{ce_1} \mu_1(y_1)dy_1 + E_2 > E_1 + E_2.$$

The first and second derivative functions of $H(x_1)$ are given by

$$\frac{d}{dx_1}H(x_1) = \begin{cases} 0 & \text{if } x_1 \leq ce_1, \\ \frac{d}{dx_1}u_1(x_1)\mu_1([x_1^m, x_1]) & \text{if } x_1 > ce_1. \end{cases}$$
$$\frac{d^2}{dx_1^2}H(x_1) = \begin{cases} 0 & \text{if } x_1 \leq ce_1, \\ = \frac{d^2}{dx_1^2}u_1(x_1)\mu_1([x_1^m, x_1]) + \mu_1(x_1)\frac{d}{dx_1}u_1(x_1) & \text{if } x_1 > ce_1. \end{cases}$$

where $\mu_1([x_1^m, x_1])$ stands for the cumulative probability of the set $[x_1^m, x_1]$, while $\mu_1(x_1)$ is the value of μ_1 at the point x_1 .

Since u_1 is strictly increasing, $\frac{d}{dx_1}u_1(x_1)\mu_1([x_1^m, x_1])$ is positive provided that $x_1 > ce_1$, which, at the same time, implies that $H(x_1)$ is strictly increasing on the interval $(ce_1, x_1^M]$. However, the concavity/convexity of $H(x_1)$ on this interval cannot be determined analytically since it depends on the particular utility and probability functions defining the corresponding expected search utility.

The function $F(x_1)$ is constant and equal to $E_1 + E_2$ on the interval $[x_1^m, \min\{x_1 \in X_1 : P^+(x_1) \neq \emptyset\}]$ if $P^+(x_1^m) = \emptyset$. If $P^+(x_1^m) \neq \emptyset$, then, for every $x_1 \in X_1$

$$\begin{aligned}\frac{d}{dx_1}F(x_1) &= \left(\frac{d}{dx_1}u_1(x_1)\right) \int_{P^+(x_1)} \mu_2(x_2)dx_2, \\ \frac{d^2}{dx_1^2}F(x_1) &= \left(\frac{d^2}{dx_1^2}u_1(x_1)\right) \int_{P^+(x_1)} \mu_2(x_2)dx_2 + u_1'(x_1) \left(\frac{d}{dx_1} \int_{P^+(x_1)} \mu_2(x_2)dx_2\right).\end{aligned}$$

Therefore, $F(x_1)$ is strictly increasing on X_1 , if $P^+(x_1^m) \neq \emptyset$. However, as was the case with the function $H(x_1)$, the concavity/convexity of $F(x_1)$ depends on the particular utility and probability functions that define it.

Consider the behavior of $H(x_1)$ and $F(x_1)$ at x_1^m

$$H(x_1^m) \stackrel{def}{=} \int_{ce_1}^{x_1^M} \mu_1(y_1)(u_1(y_1) + E_2)dy_1 + \int_{x_1^m}^{ce_1} \mu_1(y_1)(E_1 + E_2)dy_1 > E_1 + E_2.$$

$$F(x_1^m) \stackrel{def}{=} \int_{P^+(x_1^m)} \mu_2(x_2)(u_1(x_1^m) + u_2(x_2))dx_2 + \int_{P^-(x_1^m)} \mu_2(x_2)(E_1 + E_2)dx_2$$

It is easy to show that $F(x_1^m) \geq E_1 + E_2$, with $F(x_1^m) = E_1 + E_2$ when $P^+(x_1^m) = \emptyset$. Thus, $F(x_1^m) < H(x_1^m)$ when $P^+(x_1^m) \neq \emptyset$.

3.1 Existence of optimal thresholds

Clearly, the expected utility functions F and H guide the decision maker's optimal information gathering process. Assume that the information search on good J has produced x_1 as first result. Then, the decision maker will choose to continue checking good J or switching to good K according to which function, either F or H , takes the highest value at x_1 . It may also happen that she is indifferent between continuing with J and switching to K . It is reasonable to think of these indifference values as optimal information gathering thresholds.¹ Thus, X_1 turns out to be partitioned in subintervals whose values induce the decision maker either to continue checking the initial good J or to switch and start checking K .

Di Caprio and Santos Arteaga (2009) illustrate how the existence of optimal threshold values, or reversing points, in the decision maker's information gathering process can be guaranteed under common non-pathological assumptions within the g.c.e.s. For example, it can be easily shown that $H(x_1^M) \leq F(x_1^M)$, with $H(x_1^M) = F(x_1^M)$ if and only if $u_1(x_1^M) + u_2(x_2^m) \geq E_1 + E_2$. Therefore, $u_1(x_1^M) + u_2(x_2^m) < E_1 + E_2$ suffices to guarantee the existence of at least one threshold value whenever $P^+(x_1^m) = \emptyset$.

On the other hand, the $u_1(x_1^M) + u_2(x_2^m) < E_1 + E_2$ condition does not suffice to guarantee the existence of an optimal threshold value within the

¹It should be noted that our definition of information gathering threshold values does not include the x_1^m and x_1^M domain limit points since no switch in the information gathering behavior of decision makers can be guaranteed at these points.

r.c.e.s. If this condition is imposed, we would obtain $F(x_1^M|rf) < H(x_1^M|rf)$. It is easy to show that $F(x_1^m|rf) < H(x_1^m|rf)$ whenever $P^+(x_1^m) = \emptyset$. However, $H(x_1^M|rf) = F(x_1^M|rf)$ if and only if $u_1(x_1^M) + u_2(x_2^m) \geq E_1 + E_2$. Thus, we have that $F(x_1^M|rf) \leq H(x_1^M|rf)$. As a result, the existence of a threshold value within the r.c.e.s can only be guaranteed if we assume $u_1(x_1^M) + u_2(x_2^m) < E_1 + E_2$ and *impose* $F(x_1^m|rf) > H(x_1^m|rf)$.

The numerical simulations will help shedding some light on the main differences between the information gathering thresholds generated by both scenarios.

Chapter 4

Signals and learning

We proceed now to analyze the effect that positive signals regarding the distribution of characteristics on X_2 and the resulting learning process have on the optimal information gathering behavior of rational decision makers. Signals are introduced on the second characteristic space in order to intuitively separate the role played by actual observations from that played by expectations.¹ Consider, as the basic reference case and without loss of generality, the optimal information gathering behavior of the decision maker

¹This assumption brings the model closer to the basic theoretical foundations of herd-prone environments. Decision makers will be able to compare realizations, but their behavior depends also on an unobservable variable on which credible signals are received. In this regard, the credibility or strength of the signal could be assumed to depend on the reputation or any other characteristic defining the information sender, which would allow for a strategic approach to the information transmission process and the resulting choice environment.

when uniform probabilities are assumed on both X_1 and X_2 .²

We will assume that receiving a credible positive signal, θ , regarding the distribution of characteristics on X_2 implies that the probability mass accumulated on the upper half of the distribution doubles, while that on the lower half halves. Thus, given the distribution of X_2 characteristics defined by $\mu_2(x_2) = \frac{1}{\beta-\alpha}$ for $x_2 \in [\alpha, \beta]$, with $\alpha, \beta \geq 0$ and $\alpha < \beta$, the corresponding conditional density function is given by

$$\pi(\theta|x_2) = \begin{cases} \frac{3}{2(\beta-\alpha)} & \text{if } x_2 \in (\frac{\alpha+\beta}{2}, \beta] \\ \frac{1}{2(\beta-\alpha)} & \text{if } x_2 \in [\alpha, \frac{\alpha+\beta}{2}] \end{cases}$$

After receiving a positive signal, rational decision makers update their initial beliefs, given by $\mu_2(x_2)$, following Bayes' rule. Therefore, if a signal is

²Even though we will only analyze the effect that the first-order stochastic dominance resulting from the signal has for the uniform density case defined in the thesis, the analysis could be generalized to any other density function, see Chapter 6 in Mas-Colell et al. (1995). A formal analysis of the effect that observing a positive signal has on the optimal information gathering behavior of rational decision makers can be found in the appendix to the current demand section.

received, i.e. $\theta = 1$, the updated beliefs of decision makers will be given by³

$$\mu_2(x_2|\theta = 1) = \frac{\pi(\theta|x_2)\mu_2(x_2)}{\int_{X_2} \pi(\theta|x_2)\mu_2(x_2)dx_2}$$

The corresponding [Bayesian] updated $F(x_1)$ and $H(x_1)$ functions defined by decision makers after receiving a credible signal within the g.c.e.s. are given by

$$F(x_1|\theta = 1) \stackrel{def}{=} \int_{P^+(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(u_1(x_1) + u_2(x_2))dx_2 + \\ \int_{P^-(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(E_1 + E_{2|\theta=1})dx_2$$

and

$$H(x_1|\theta = 1) \stackrel{def}{=} \int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_{2|\theta=1})dy_1 + \\ \int_{Q^-(x_1)} \mu_1(y_1)(\max\{u_1(x_1), E_1\} + E_{2|\theta=1})dy_1$$

with

$$P^+(x_1|\theta = 1) = \{x_2 \in X_2 \cap \text{supp}(\mu_2) : u_2(x_2) > E_1 + E_{2|\theta=1} - u_1(x_1)\},$$

$$P^-(x_1|\theta = 1) = \{x_2 \in X_2 \cap \text{supp}(\mu_2) : u_2(x_2) \leq E_1 + E_{2|\theta=1} - u_1(x_1)\}$$

³This process can be assumed to continue as rational decision makers keep on updating their beliefs using Bayes' rule after receiving further signals. For example, a second signal, providing decision makers with the same qualitative information, i.e. $\theta = 2$, would lead to a second Bayesian updating process and the following distribution of beliefs on X_2

$$\mu_2(x_2|\theta = 2) = \frac{\pi(\theta|x_2)\mu_2(x_2|\theta = 1)}{\int_{X_2} \pi(\theta|x_2)\mu_2(x_2|\theta = 1)dx_2}.$$

and the same $Q^+(x_1)$ and $Q^-(x_1)$ sets as those defined in the unsigaled case, since X_1 and $\mu_1(X_1)$ remain unaffected by the signal received.

It can be easily shown analytically that if $\mu_2(x_2|\theta = 1)$ first-order stochastically dominates $\mu_2(x_2)$, then both $F(x_1|\theta = 1) \geq F(x_1)$ and $H(x_1|\theta = 1) \geq H(x_1)$. Note that, if $\mu_2(x_2|\theta = 1)$ first-order stochastically dominates $\mu_2(x_2)$, then, by definition, $E_{(2|\theta=1)} \geq E_2$. This is the effect that the updated $\mu_2(x_2|\theta = 1)$ density generated by the signal has on the $F(x_1)$ and $H(x_1)$ functions through the new induced value $E_{(2|\theta=1)}$. It trivially follows that

$$\frac{dH(x_1)}{dE_2} = 1 > 0.$$

Therefore, the direct dependence of $H(x_1)$ on E_2 leads to an upward shift of the function if the value of E_2 increases after the signal is received.

Regarding the $F(x_1)$ case, the increase in $E_{(2|\theta=1)}$ results in the set $P^+(x_1|\theta = 1)$ shrinking with respect to $P^+(x_1)$, while $\mu_2(x_2|\theta = 1) \geq \mu_2(x_2)$ over the newly defined $P^+(x_1|\theta = 1)$ interval. Applying Leibnitz's rule to $\frac{dF(x_1)}{dE_2}$ while keeping $\mu_2(x_2)$ fixed would allow us to isolate the effect that changes in the E_2 value have on the $F(x_1)$ function. It follows that

$$\left. \frac{dF(x_1)}{dE_2} \right|_{\mu_2(x_2)} = \int_{x_2^m}^{u_2^{-1}(E_1+E_2-u_1(x_1))} \mu_2(x_2) dx_2 > 0, \forall x_1 \in X_1, \text{ iff } P^-(x_1^M) \neq \emptyset.$$

Thus, coupling a signal-based increment in E_2 with a first-order stochastic dominance spread on $\mu_2(x_2)$ would lead to an increase of the $F(x_1)$ function $\forall x_1 \in X_1$. Note that, if either $E_{(2|\theta=1)} \geq E_2$ or $P^-(x_1^M) = \emptyset$, or both, the first order stochastic dominance on $\mu_2(x_2)$ guarantees that $F(x_1|\theta = 1) \geq F(x_1)$ for all x_1 values in X_1 .

The [Bayesian] updated $F(x_1|rf)$ and $H(x_1|rf)$ functions defined by decision makers after receiving a credible signal within the r.c.e.s. follow directly from $F(x_1|\theta = 1)$ and $H(x_1|\theta = 1)$ in the exact same way $F(x_1|rf)$ and $H(x_1|rf)$ followed from $F(x_1)$ and $H(x_1)$. However, the effect that the updated $\mu_2(x_2|\theta = 1)$ density has on the $F(x_1|rf)$ and $H(x_1|rf)$ functions differs significantly from that of the g.c.e.s. Once again, it is trivial to show that

$$\frac{dH(x_1|rf)}{dE_2} = \int_{Q^+(x_1)} \mu_1(y_1)dy_1 + \int_{Q^-(x_1|rf)} \mu_1(y_1)dy_1 \in (0, 1).$$

However, the effect that the signal has on $F(x_1|rf)$ is slightly more cumbersome. Once again, applying Leibnitz's rule to the definition of $F(x_1|rf)$ while keeping $\mu_2(x_2)$ fixed allows us to isolate the effect that changes in the E_2 value have on the $F(x_1|rf)$ function

$$\begin{aligned} \left. \frac{dF(x_1|rf)}{dE_2} \right|_{\mu_2(x_2)} = \\ -[\mu_2(u_2^{-1}(E_1 + E_2 - u_1(x_1)))(E_1 + E_2)] \frac{d}{dE_2} [u_2^{-1}(E_1 + E_2 - u_1(x_1))] < 0. \end{aligned}$$

Note that the initial shock induced by the signal on $F(x_1|rf)$ is negative. That is, an increase in the value of E_2 has a negative effect on the incentives of decision makers to gather the next piece of information from the good whose first characteristic has been observed. The intuition for this result is straightforward. Requiring relatively higher X_2 realizations to compensate for the higher value of $E_{(2|\theta=1)}$ constitutes a serious drawback when the certainty equivalent good is not guaranteed. This is the case despite the first

order stochastic dominance exhibited by the $\mu_2(x_2|\theta = 1)$ probability function. This negative effect will become evident in the corresponding numerical simulations, where further intuition will be provided.

4.1 Climbing the quality ladder

Decision makers shift from unsignaled to signaled markets in order to try to improve upon an observed good through their information gathering process. That is, given the existing technology, to which the decision maker has grown accustomed to in the unsignaled market, her incentives to shift the information gathering process to the signaled market depend on whether or not the technological development introduced allows her to improve upon the existing product characteristics. In this regard, Eng and Quaia (2009) present a review of the literature illustrating how continuous customer learning and education are essential as firms need to communicate the benefits of a new product or technology to customers and reduce their perceived risks and uncertainties of an innovations. More precisely, when modeling sophisticated customers within the computer industrial structure, Malerba et al. (2003: 8) refer to them as those customers who “won’t buy a new model computer unless it is as good as or better than the old model ones”.

As a result, three different types of decision processes will be analyzed when defining the transition between markets. Each process leads to its own $H : X_1 \rightarrow \mathbb{R}$ functional form based on the improvement upon the observed characteristics that may be attained when decision makers shift

their information gathering processes between markets.

4.1.1 Decision irreversibility

In this case, if the decision maker shifts her information gathering process to the signaled market, she will have to forego any information obtained in the unsignaled one. Hence, a shift to the signaled market constitutes an irreversible decision, and her final choice, if any, must be made within the set of goods available in the signaled market. The corresponding $H(x_1)$ function is given by the expected value derived from observing one characteristic in the signaled market, endowed with a higher E_2 than the unsignaled one,

$$H(x_1|nr) \stackrel{def}{=} \int_{E_1}^{x_1^M} \mu_1(y_1)(u_1(y_1) + E_{2|\theta=1})dy_1 + \int_{x_1^m}^{E_1} \mu_1(y_1)(E_1 + E_{2|\theta=1})dy_1.$$

Note that the integration intervals differ with respect to the $H(x_1)$ case defined previously for the unsignaled market. That is, the decision maker aims at observing a characteristic above E_1 in the signaled market or choosing randomly within it otherwise, and is unable to guarantee a given x_1 value due to the irreversibility assumption and the unique observation she has left. If signals are not technologically neutral, then $\frac{\partial H(x_1)}{\partial E_2} > 0$, implying that $H(x_1|nr) > H(x_1)$, $\forall x_1 \leq ce_1$. However, as the numerical simulations will show, this effect does not suffice to generate a shift to the signaled market for all x_1 values in X_1 . The utility loss caused by the irreversibility effect dominates the transition incentives triggered by a higher E_2 value for large x_1 realizations.

4.1.2 Guaranteed improvement

The second scenario combines the previous *decision irreversibility* framework with an explicit guarantee, issued by the signaler, of providing a good whose first characteristic is at least as high as that observed in the unsignaled market, i.e. $x_{1|\theta=1} \geq x_1$, if the decision maker shifts her information gathering process to the signaled one. If the decision maker is aware of and trusts such an announcement, then the corresponding $H(x_1)$ would be given by

$$H(x_1|fg) \stackrel{def}{=} \int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_{2|\theta=1})dy_1 + \int_{Q^-(x_1)} \mu_1(y_1)(\max\{u_1(x_1), E_1\} + E_{2|\theta=1})dy_1.$$

Clearly, this function constitutes an expected utility improvement upon the $H(x_1)$ defined in the unsignaled market $\forall x_1 \in X_1$ due to the $E_{2|\theta=1} > E_2$ effect. Other than that, its structure and interpretation are identical to those of the $H(x_1)$ defined for the unsignaled market.

4.1.3 Reversibility

The third scenario assumes that the transition of the information gathering process between markets is reversible. That is, after gathering an observation from the unsignaled market the decision maker may shift her information gathering process to the signaled one and, if the observation attained in this market is not sufficiently good, return to the unsignaled market, where the

observed x_1 is guaranteed [though coupled with a lower E_2 value].⁴ This assumption leads to the following $H(x_1)$ function

$$H(x_1|r) \stackrel{def}{=} \int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_{2|\theta=1})dy_1 + \int_{Q^-(x_1)} \mu_1(y_1) \max\{(\max\{u_1(x_{1|\theta=1}), E_1\} + E_{2|\theta=1}), (\max\{u_1(x_1), E_1\} + E_2)\} dy_1.$$

Note that the integration intervals are identical to those of $H(x_1)$ in the unsignaled case, since the point of reference defining the $Q^+(x_1)$ and $Q^-(x_1)$ sets remains the observed x_1 value in the unsignaled market.

The first expression on the right hand side of $H(x_1|r)$ resembles the one defined for $H(x_1)$ in the unsignaled market. In this case, if the decision maker observes a first characteristic in the signaled market higher than the x_1 from the unsignaled one, then, since $E_{2|\theta=1} > E_2$, she will shift her information gathering process to the good observed in the signaled market [and purchase it].

The second right hand side expression states that the decision maker prefers [to gather information on] the good whose first characteristic has been observed in the signaled market as long as its expected utility value remains above that of the good whose x_1 has been observed in the unsignaled one. If its expected utility falls below, the decision maker will shift her information

⁴The ability of decision makers to compare the goods observed in the signaled and unsignaled markets when designing their information gathering algorithms may be interpreted as a property partially reflecting the “frustrated memory” characteristic of the genetic algorithm defined by Aversi et al. (1999).

gathering process to the unsignaled market. This expression requires some additional explanations.

Consider the case where the first characteristic observed in the unsignaled market is below ce_1 . If this were the case, then the good that the decision maker expects to observe in the unsignaled market [if she uses her second piece of information to gather an observation from this market] provides her with an expected utility given by

$$H(x_1|nr) \stackrel{def}{=} \int_{ce_1}^{x_1^M} \mu_1(y_1)(u_1(y_1) + E_2)dy_1 + \int_{x_1^m}^{ce_1} \mu_1(y_1)(E_1 + E_2)dy_1,$$

which is lower than $H(x_1|nr)$.⁵ Therefore, if the x_1 observed in the unsignaled market is below ce_1 , the decision maker has an incentive to shift her information gathering process to the signaled one.⁶

Consider now the case where the first characteristic observed in the unsignaled market is above ce_1 . If this were the case, gathering a first observation from the signaled market, denoted by $x_{1|\theta=1}$, such that

$$u_1(x_{1|\theta=1}^*) = u_1(x_1) + E_2 - E_{2|\theta=1},$$

would leave the decision maker indifferent between gathering an additional piece of information from either the signaled or the unsignaled market. Observing a $x_{1|\theta=1}$ value (below) above $x_{1|\theta=1}^*$ would shift her gathering process

⁵Note that $H(x_1|nr)$ defines the expected utility derived from the good that the decision maker expects to observe in the signaled market [if she uses her second piece of information to gather an observation from this market].

⁶In this case, $H(x_1|r) = H(x_1|nr)$.

towards the (un)signaled market. Clearly, the higher expected utility derived from the second signaled characteristic generates an interval defined by the difference $E_{2|\theta=1} - E_2$ such that any $u_1(x_1) - u_1(x_{1|\theta=1}^*)$ distance smaller than this difference would not suffice to compensate for the signal effect and would lead the decision maker to bias her information gathering process towards the signaled market.

In summary, if the decision maker observes $x_{1|\theta=1} > x_1$, then she should continue gathering information in the signaled market. If, on the other hand, $x_{1|\theta=1} < x_1$, then she should proceed according to the maximum expected value derived from either remaining in the unsignaled market, with a higher x_1 and a lower E_2 , or shifting to the signaled one, with a lower $x_{1|\theta=1}$ but a higher $E_{2|\theta=1}$.

4.2 Numerical simulations: credible signals, information gathering herds and stricter continuation criteria

Decision theoretical models, mainly in their economic and operational research variants, generally assume risk neutral decision makers. Even though the analytical simplifications derived from such an assumption are substantial, the consequences are far from innocuous. Therefore, simulations will be provided for both risk neutral and risk averse decision makers, while keep-

ing in mind that a potentially large set of possible scenarios can be studied numerically following the theoretical setting introduced through the thesis.

The numerical sections of the thesis will present several simulations that illustrate the behavior of the optimal threshold values as decision makers receive credible signals indicating the existence of a technologically superior set of goods while being subject to the information gathering constraints imposed within each respective subsection. Throughout the simulations, decision makers will be assumed to have a well-defined preference order both *within* and *among* characteristics. That is, the first characteristic will be assumed to be more important for decision makers and, therefore, lead to a higher expected utility than the second one.⁷ Besides, in order to facilitate comparisons among the threshold values generated by different numbers of signals and types of decision makers, the support of all the probability functions will be kept unchanged through the simulations.

In all two dimensional figures the horizontal axis represents the set of x_1 realizations that may be observed by the decision maker, with the corresponding subjective expected utility values defined on the vertical axis and the certainty equivalents explicitly identified through a vertical line.

Figure 1 illustrates the one and two signals cases, denoted by 1s and 2s,

⁷In other words, rational decision makers subject to information acquisition constraints of any type will be assumed to base their information gathering process on the subjective importance of the characteristics that can be observed. The intuition justifying this assumption follows from the consumer choice literature dealing with multi-attribute sequential search processes, see Bearden and Connolly (2007).

respectively, and the evolution of the corresponding threshold values within a basic risk neutral scenario. Points A , B and C identify the threshold values defined by decision makers when gathering information on a set of goods located within the unsignaled, one signal and two signals markets, respectively. Figure 2 illustrates the same environment as Figure 1 but within a risk averse setting, where the utilities with which decision makers are endowed have been shifted from basic linear functions to square roots.

Clearly, positive signals generating first order stochastic dominant beliefs lead to higher expected utility levels for all possible x_1 values. However, in doing so, signals shift the respective optimal threshold values towards higher x_1 realizations.

The intuition arising from these results states that positive signals should generate immediate herds of consumers towards the subset of goods on which they are defined, but, at the same time, decision makers, who expect a higher E_2 value to be guaranteed from their information gathering process, become less search averse within the corresponding subset, i.e. the area where the H function remains above the F one increases for relatively low x_1 realizations. As a result, decision makers would require relatively higher realizations from the first characteristic space in order to continue gathering information on the observed good.

Such an effect can also be observed in the risk averse setting illustrated in Figure 2. Note, however, the increase in search aversion relative to the linear risk neutral case, an effect already described by Di Caprio and Santos

Arteaga (2009). Thus, as risk aversion increases, an increase in the information gathering continuation area follows. Other than that, the signal effects are identical to those observed in the risk neutral case.

The main implicit assumptions defining the current setting, i.e. signal credibility, and the absence of both search frictions and consumption inertia, have been imposed to reflect the frictionless environment required for decision makers to generate an information gathering herd after becoming aware of the existence of a set of technologically superior products.⁸ However, the presence of search frictions and basic consumption inertia implies that the information gathering transition between markets is not necessarily guaranteed, even if signal credibility is maintained. The following section illustrates this type of theoretical setting.

⁸We have just seen that, even in this case, the resulting herd does not necessarily lead to faster adoption within the set of signaled goods.

Chapter 5

Search and matching frictions

The previous subsection has analyzed numerically the effects that positive signals and changes in the curvature of the utility function assigned to the decision maker have on her optimal information gathering behavior. The resulting search aversion derived from increments in the risk aversion coefficient of decision makers was obtained absent search frictions of any type. However, the existence of search and matching frictions is known to condition the optimal search behaviour of decision makers. Even though the effect that frictions may have on the behavior of $H(x_1)$ is intuitively clear, this section provides the theoretical basis for its posterior simulation.

Consider a decision maker who has just checked the first characteristic of a given good, x_1 , and must decide whether to check the second characteristic from the same good or start searching for a second good on which to gather information. It will be assumed that the probability that retrieving the next

observation from a new good pays off, meaning that at least l within m available goods satisfy the *inherent* search parameters fixed by the decision maker, is given by the following cumulative binomial distribution

$$\psi(m, l, f) = \sum_{j=l}^m \binom{m}{j} f^j (1-f)^{m-j},$$

where f represents the probability assigned by the decision maker to the fact that a good satisfies her subjectively defined requirements.

Even though the search process allows the decision maker to observe the current [observable, as redundant as it may be] characteristics of a good, other inherent characteristics remain directly unobservable and will either become apparent after purchasing the good or must be subjectively forecasted by the decision maker. The former problem was identified by Nelson in 1970. He stated that while prices are directly observable, other characteristics defining the overall quality of goods require consumption. Search processes must therefore be defined by price and experience components, the latter requiring the actual consumption of the good to be observed, see Nelson (1970). The latter problem relates to the existence of network, lock-in and bandwagon effects in the consumption process of goods, see Geroski (2000) for a review of the literature. That is, while current goods have a established network of connections and are largely compatible with other existing products, newly introduced products may fail to develop such a quality.

Given the large variety of products available to observe and purchase, the decision maker must add to her search process a matching probability

accounting for her expectation of what percentage from the newly introduced goods will indeed satisfy her future network requirements, i.e. f would be the subjective probability associated by the decision maker to any of the new goods achieving the status of or becoming as widespread [diffused] as the currently available ones. Given this probability, the decision maker requires a minimum percentage of the newly introduced goods expected to develop [achieve] a sufficiently large network [diffusion] to become available during the search process.¹ These effects are particularly important when considering the evolution and diffusion of increasingly complex technological products. A basic recent example would be given by the set of available e-books and the respective formats they are compatible [and incompatible] with.

Thus, the probability of finding a second good that matches the required inherent characteristics defined by the decision maker is given by $\psi(m, l, f)$. The expected payoff obtained from remaining checking the first good is $F(x_1)$, while that of starting gathering information on a second signaled good must consider the search and matching frictions defined above and is therefore given by $\psi(m, l, f) H(x_1|\cdot)$. As a result, the transition between unsig-

¹Note that $\psi(m, l, f)$ combines the standard textbook approach to technology spreads and learning from Aghion and Howitt (1998), given by the cumulative binomial form of the function, and a matching process commonly used in the economic search literature, see McCall and McCall (2008). In this way, the subjective diffusion expectations implicitly defined within f are separated from the minimum friction requirements imposed on the search process via l and m .

and signaled markets will be based on the following comparison

$$F(x_1) \geq \psi(m, l, f) H(x_1 | \cdot).$$

The numerical simulations introduced through the following subsection will combine changes in both search and matching frictions to illustrate the main transition results obtained. Clearly, the interpretation of the results differs depending on the friction effect that one wants to emphasize. We will refrain from doing so and concentrate on the general effect that market frictions have on the optimal information gathering behavior of decision makers.

5.1 Numerical simulations: search frictions, consumption inertia, multiple thresholds and decision reversibility

The current search and matching frictions setting has been explicitly designed to capture the effects that habits and consumption inertia have in the information gathering process of decision makers. That is, the existence of search and matching frictions provides a natural framework for decision makers to also exhibit inertia, a condition much harder to justify intuitively within the previous [pure] herding environment, where the $H(1s)$ function remains above $F(ns)$ for all $x_1 \in X_1$. In this sense, observing a signal whose intensity or strength is weakened by the existing frictions, such that the resulting

$H(1s)$ function crosses $F(ns)$ at some $x_1 \in X_1$, allows for a straightforward justification of the inertia assumption.² In the current setting, such an assumption implies that despite the recognized technological superiority of the set of signaled goods, decision makers may be initially reluctant to shift their information gathering processes to the signaled market and, therefore, they gather their first observation from the unsignaled one.

We allow for habits and consumption inertia in order to account for the fact that the existence of a technologically superior set of goods does not necessarily imply an immediate transition to the market generated by the newly introduced technology, see, for example, Geroski (2000) and the literature cited within it. Moreover, as emphasized by Malerba et al. (2003), the introduction of a new product within a given industry relies on the existence of experimental consumers that may allow for its survival through the creation of specialized niche markets. In this sense, the degree of experimentation exhibited by a consumer could be assumed to be implicitly defined within or approximated by $\psi(m, l, f)$.

The following results summarize our main numerical findings regarding the effects that search and matching frictions together with consumption

²The existence of network effects could also provide the required intuition, as it is always challenging for decision makers to be among the first consumers of a new technology while abandoning an already established one. The next theoretical setting will analyze this possibility in further detail. Note, however, that the rational sophistication required from decision makers in order to account for the dynamic evolution of different sets of goods will make the analysis more plausible if it is considered from the supply side.

inertia may have on the optimal information gathering behavior of decision makers.

Lemma 5.1.1 *If the information gathering process of decision makers is subject to search and matching frictions, then the information gathering transition between markets may not occur. This is the case even if the signaling firm guarantees the x_1 characteristic observed within the unsignaled market.*

Lemma 5.1.2 *If multiple transition equilibria exist, the signaling firm may be forced to guarantee relatively high x_1 values to trigger the transition between markets. In this case, a market reversal in the information gathering process may take place for relatively high x_1 values.*

The results described in these lemmas follow from Figures (3) to (7), where different friction intensities have been simulated for a given identical signal. These simulations illustrate how if, for example, brand education helps reducing (or creating) search frictions, see Eng and Quaia (2009), then incumbent firms may have a considerable advantage over newcomers when the latter try to introduce a technologically superior product in the market.³ Note that this is the case despite the fact that the definition of $H(x_1|\theta =$

³Similarly, frictions affecting the strength or intensity of the signal could be assumed to be a function of the reputation of the firm signaling, which would provide well reputed incumbents with a considerable advantage over relatively unknown newcomers. Indeed, as the simulations show, the [information gathering] transition probability to the signaled market should be a *non-increasing* function of these frictions.

1) assumes implicitly that the signaling firm provides the decision maker with a good whose first characteristic is at least as high as that observed in the unsignaled market, i.e. $x_{1|\theta=1} \geq x_1$, if she shifts her information gathering process to the signaled one. When compared with the basic herding setting defined in the previous section, we see that search frictions or their absence, lock-in effects or preference for diversified information, and customer education or learning bounds, could all be respectively assumed to bias the information gathering process of decision makers in favor of the current or the previous setting, respectively.⁴

Two main conclusions follow from these simulations. The first one has already been stated in the latter Lemma. That is, the existence of search and matching frictions may force newcomers to improve upon very high x_1 characteristics displayed by the set of incumbent goods in order to enter the market [with a set of technologically superior products]. The second one is the fact that a set of mediocre products offered by the incumbent may sur-

⁴Fontana and Guerzoni (2007) illustrate empirically how if interacting with customers helps reducing uncertainty, then firms with a high propensity to interact are more innovative and tend to introduce product innovations. These findings help emphasizing the importance of consumer education in reducing search and matching frictions among decision makers. In a related environment, Corrocher and Zirulia (2010) consider innovations in mobile communication services and show how demand provides both incentives to innovate and information about the behavior of users when innovating within an uncertain context. In particular, they find that the customer base plays an important role in shaping firm's strategies in terms of the number and characteristics of new tariff plans.

vive the entry of technologically superior ones, an equilibrium phenomenon that worsens with the strength of the frictions. That is, if the decision maker observes a x_1 characteristic in the unsignaled market located just above or below ce_1 , then she may have an incentive to remain gathering information within this market independently of the technological improvement introduced by the signaling firm. In this case, frictions constitute such a serious drawback for the decision maker that the higher $E_{2|\theta=1}$ value expected within the signaled market does not compensate for their negative effect on her information gathering process. Once again, this occurs despite the signaling firm guaranteeing a good with a x_1 characteristic at least as high as the one observed in the unsignaled market. On the other hand, the $E_{2|\theta=1}$ and guaranteed x_1 effects *may* prevail over the search frictions one if relatively high x_1 realizations are observed, leading to the information gathering reversals described in Lemma 5.2.

Finally, note that Figures 3 and 6 illustrate how identical search frictions may generate multiple transition equilibria within the risk neutral case but not within the risk averse one. This type of result follows from the stricter continuation criteria that risk neutrality gives place to relative to risk aversion, an effect that we defined as search aversion in the previous section.

We have illustrated how their sets of available goods may provide incumbent firms with a significant advantage over newcomers due, among others, to lock-in, bandwagon, network and reputation effects.⁵ However, these effects

⁵Bandwagon and network effects are also formally discussed and incorporated by

have been assumed to be implicitly defined within a subjective cumulative probability function, $\psi(m, l, f)$, lacking the explicit dynamic diffusion properties that these effects generally account for, see Geroski (2000). The following section studies the influence that network (bandwagon and reputation) effects and the corresponding diffusion processes have on the acquisition *and the introduction* of technologically superior goods within a given market.

Malerba et al. (2003) in their behavioral evolutionary model of demand.

Chapter 6

Technology diffusion and network effects

The third type of basic setting analyzed numerically considers the market introduction of technologically superior products from the point of view of the supplier.¹ The intuition justifying this change in perspective follows from the fact that, after all, it is firm's managers [and not simply firms,

¹Alternatively, this setting could also be interpreted as the *acquisition* of technologically superior products by highly sophisticated decision makers, i.e. users in the sense of von Hippel (1988). If we were to follow this alternative interpretation, it should be emphasized that the psychological and sociological characteristics of the environment affecting the preferences of and choices made by decision makers change as the product evolves, a problem accounted for in marketing and sociology, but seldom by the economic literature, with exceptions from its evolutionary branch such as Aversi et al. (1999), Rogers (2003), Fatas-Villafranca and Saura-Bacaicoa (2004), and Malerba et al. (2007), among others.

as the industrial economics literature seems to insist upon] the theoretical entities who, based on their available information, decide whether or not to introduce a given technology in the market, a fact that the recent literature on knowledge economics and management recognizes and accounts for, see Foray (2004) and Holsapple (2003) for a review of the respective literatures.² Moreover, the evolutionary economic literature has also started to delve into the strategic choices directly faced by firm's managers within the existing markets for technology and knowledge, see Arora et al. (2001a).

Therefore, diffusion processes and network effects will be considered from the point of view of a manager deciding whether or not to introduce a technologically superior good in the market based, for example, on the market share or the compatibility with the products developed within other market sectors that the good is expected to attain within a given time frame. In this case, the expectations of decision makers (managers) regarding the type of diffusion process under consideration and their forecasted evolution of possible complementary or substitute products become extremely important.

The current setting has been developed to illustrate an important point

²In this regard, when analyzing the adoption of a new product within their demand based model, van den Ende and Dolfsma (2005, 87) assign the decision making role to a firm. The authors justify their choice as follows: "Final consumers are different from firms which choose to acquire a product, even if it is the same product. Decision-making processes of firms are more rational, as for firms more time lapses between a decision and the actual behaviors. Still, the perceived rationality of decision-making processes in firms should not be overestimated."

made by Geroski (2000) when analyzing the main patterns generally believed to determine the behavior of diffusion processes and the crucial importance that initial conditions and choices have on the evolution of the technological diffusion path: “When the initial choice between A and B is made quickly and clearly and when A is clearly superior to the existing technology, then diffusion is likely to be rapid (quick and decisive decision making will quickly stampede the herd into action). If, however, these early choices are muddled, then the processes which generate and swell an information cascade are likely to be fragmented and weak”, see Geroski (2000, 620).

We will consider two main diffusion [epidemic] processes, widely employed both in biology and by the evolutionary economic literature, used by Geroski (2000) to analyze the apparently slow speed at which firms adopt new technologies. One of them is based on a central diffusion source while the other relies on a word of mouth non-centralized communication process.

- (i) Out of a normalized population of potential users, denote by $\Psi_a(t)$ the percentage of decision makers who have either adopted the technologically superior product at time t or are aware of its existence, while those who have not yet adopted it or are unaware of its existence are defined by $\Psi_n(t) = 1 - \Psi_a(t)$. Assume that information is transmitted from a central source, reaching a percentage α of the population who has not yet adopted the technology or is unaware of its existence at time t . If information is received over the time interval Δt , adoption or awareness increases by an amount $\Delta\Psi_n(t) = \alpha(1 - \Psi_a(t))\Delta t$ during

this period. The solution of this difference equation as $\Delta t \rightarrow 0$ is given by (see any textbook on the subject, for example, Braun (1983))

$$\Psi_a(t) = 1 - e^{-\alpha t}, \quad t \in [0, T]$$

Geroski (2000) relates this type of diffusion process to the transmission of information regarding the existence of, for example, a new hardware. However, he emphasizes the fact that this type of process may not be accurate when accounting for the information flows about the associated software. In this case, a word of mouth information diffusion process must be considered.

- (ii) Assume that each adopter or decision maker aware of the existence of a technologically superior product contacts a non-adopter or unaware decision maker with probability β . The probability that contact is made with any non-adopter [unaware decision maker] at time t is given by $\beta\Psi_a(t)$. Thus, the percentage of adopters [aware decision makers] increases over the Δt time interval by the amount $\Delta\Psi_a(t) = \beta\Psi_a(t)(1 - \Psi_a(t))\Delta t$. The solution of this difference equation as $\Delta t \rightarrow 0$ is given by

$$\Psi_a(t) = \left(1 + \left(\frac{1}{\Psi_a(0)} - 1\right)e^{-\beta N t}\right)^{-1}, \quad t \in [0, T]$$

where $\Psi_a(0)$ is the proportion of adopters or aware decision makers existing at time zero and N is the total number of decision makers composing the market.

Consider now the effects that different types of diffusion processes may have on the optimal information gathering and choice behavior of decision makers. In particular, a sophisticated decision maker must decide whether or not to proceed with the introduction or the adoption of a technologically superior product based on the factors defining the speed and type of diffusion process under consideration. Following a similar intuitive description to the one used in the search and matching frictions scenario, the information gathering transition between markets will be based on the following comparison

$$F(x_1) \geq \Psi_a(t)H(x_1|\cdot), \quad t \in [0, T].$$

Clearly, different dynamic forecasts resulting from different diffusion processes would lead to different threshold reference values and to goods being accepted or rejected depending on their expected [market] spread velocity. That is, relatively faster spreads imply that $H(x_1|\cdot)$ surpasses $F(x_1)$ for all $x_1 \in X_1$ within relatively shorter periods of time.

An obvious alternative interpretation of $\Psi_a(t)$ could be made in terms of the expected compatibility of the product under consideration with the set of complementary [and substitute] goods existing within other market sectors. In this regard, Arora et al. (2001b) emphasize the importance that markets for technology have for the strategic management of firms.

Finally, note that the current setting provides an alternative theoretical framework to the generalized Polya urn decision theoretical environment defined by Kornish (2006) when analyzing the effect that different network and

diffusion processes have on the choice and timing of technology.

6.1 Numerical simulations: diffusion and network effects

The numerical simulations presented in Figures 8 and 9 illustrate how different expected diffusion patterns determine the decision of whether or not to introduce [acquire] a technologically superior product in [from] the market.³ Thus, depending on the expected type of diffusion [compatibility] process under consideration, some firms may decide to introduce [acquire] a product or wait for further suppliers [adopters] to take on the technology and then proceed. Clearly, highly educated consumers in the sense of Eng and Quiaia (2009) may be assumed to promote faster spreads and guarantee higher profits during longer periods of time due to educational lock-in and brand loyalty effects. As a consequence, subjective forecast differences among decision makers regarding the evolution of $\Psi_a(t)$ would be responsible for the emergence and stability of technological niche markets within the current theoretical setting.⁴ In other words, the emergence and stability of techno-

³Note that these figures constitute a dynamical version of Figures 3 to 7.

⁴Dolfsma and Leydesdorff (2009) emphasize the pervasive effects of lock-in and exemplify how if network externalities among adopters are reinforced by the market, then the development of a new generation of technologies may be irrelevant to the techno-economic system which prevails. Together with markets and technology, these authors consider political decision making as a third selection mechanism that may allow for breaking-out

logical niche markets [introduction and prevalence of a product] within the current environment could be intuitively justified in several ways.

First, as Malerba et al. (1999, 2001) illustrate, the main advances in component technologies driving the evolution of the computer industry were developed by newcomer firms that managed to survive by supplying experimental consumers in technological niche markets. In this regard, Malerba et al. (2003, 2007) highlight the fact that incumbents have been shown by the descriptive literature to be subject to cognitive biases and organizational factors that play a major role in accounting for the fatal lag in their response when the new technology succeeds in getting a foothold. That is, an incorrect estimation of $\Psi_a(t)$ and the corresponding gains derived from introducing [acquiring] a technologically superior product by the incumbent firm, i.e. miscalculating the payoffs and, therefore, the stability of the technological niche market, could lead to the creation of stable technological niche markets by a newcomer with a different estimation of $\Psi_a(t)$ and its dynamic evolution. Accounting for network and bandwagon effects [as our decision makers are assumed to do] requires defining several possible diffusion pro-

from a given technological trajectory. Though the explicit introduction of decision makers brings our model closer to theirs, there exists a fundamental difference between both. That is, Dolfsma and Leydesdorff (2009) state that their main argument does not depend on assumptions about the characteristics of a technology, nor on the extent to which agents' knowledge is perfect or complete. Besides, they do not account for the possibility of decision makers responding to their [social] environment, while our model implicitly allows for this type of scenario.

cesses subjectively, which may greatly differ between firms and significantly modify their expected payoffs and subsequent decisions.

Second, the existence of vintage effects, see Bohlmann et al. (2002), implies that later entrants utilizing improved technology can face lower costs and reach higher quality levels than the pioneer signaling firm. These authors show that pioneers in categories with high vintage effects tend to have lower market shares and higher failure rates. Moreover, they find key relationships between the magnitude of the pioneer advantage [or disadvantage] and the consumer valuation of product attributes such as variety and quality. In particular, their empirical results illustrate how pioneers do better in product categories where variety is more important and worse in categories where product quality is more important. In this regard, we could argue that differences in the communication and diffusion patterns determining $\Psi_a(t)$ may arise depending on the type of attribute under consideration, as Geroski (2000) did at the product level when defining the hardware versus software example described above.

Third, if instead of using the percentage of potential adopters as the main variable defining the diffusion equation, we use the technological development level of either competitors or subsidiaries, we could allow for a formal representation of the strategic interactions existing behind the formation of markets for technology, see Arora et al. (2001b). Similarly, we could assume that $\Psi_a(t)$ represents the expected development of the technological requirements that must be mastered by a firm or its competitors in order to enter

a market. Both these interpretations must be based on the heterogeneously formed expectations of firm's managers, which will result in different $\Psi_a(t)$ being considered when defining the strategies of the corresponding firms.

Finally, note that $\Psi_a(t)$ could also be assumed to reflect the influence that different types of policies have on the decision making processes [and incentives] of both firm's managers and consumers. For example, fiscal policies could be used to discriminate among products or to establish an early product demand base in order to guide the market in a particular direction. Moreover, sectoral characteristics may also determine the adoption process of technological change. These features would range from the capacity to reap the rewards arising from technological progress, which varies among technological regimes, to the existence of intermediaries between the supply and demand sides, such as doctors within the market for prescription drugs. Clearly, these, and many other environmental features, may be included to account for possible changes in the behavior of $\Psi_a(t)$ and their effect on the evolution of technological niche markets.

Chapter 7

Guaranteed versus refused certainty equivalents

7.1 Numerical simulations: basic decision environment

Consider, as the basic reference case, the optimal information gathering behavior that follows from the standard risk neutral utility function represented in Figure 10. Figure 14 illustrates the same environment as Figure 10 but within a risk averse setting, where the utilities with which decision makers are endowed have been shifted from basic linear functions to square roots. Clearly, as the degree of risk aversion increases, the support area on which the function $H(x_1)$ remains above the function $F(x_1)$ vanishes. Thus, the

degree of risk aversion does not only affect the calculation of certainty equivalent values but also the willingness to search of rational decision makers. That is, as the coefficient of relative risk aversion increases, decision makers become more reluctant to start a new search for a good better than the one whose first characteristic has already been observed.

The optimal behavior described in Figures 10 and 14 corresponds to the guaranteed certainty equivalent scenario. Figures 11 and 15 illustrate how when considering the refused certainty equivalent scenario the set of X_1 realizations such that $F(x_1) > H(x_1)$, i.e. such that decision makers prefer to remain gathering information on the good whose first characteristic has been observed instead of starting gathering information on a new good, becomes a proper subset of the one defined within the g.c.e.s.. Note also that refusing to make a random purchase from the set of available goods generates three different information gathering subintervals and a discontinuity in the $H(x_1)$ function within both the risk neutral and risk averse scenarios. The main conclusion that may be initially derived from this basic environment is that any [endogenous or exogenous] constraint preventing decision makers from making a random purchase generates a much stricter set of continuation criteria among the corresponding set of goods. The signaling setting described in the following section will allow us to elaborate on this result.

7.2 Numerical simulations: market signals

Figure 1 illustrates once again the one and two signals cases, denoted by 1s and 2s, respectively, and the evolution of the corresponding threshold values within a basic risk neutral g.c.e.s..¹ Clearly, positive signals generating first order stochastic dominant beliefs lead to higher expected utility levels for all possible x_1 values. However, in doing so, signals shift the respective optimal threshold values towards higher x_1 realizations. As already stated, the intuition arising from these results states that positive signals should generate immediate herds of decision makers towards the subset of goods on which they are defined, but, at the same time, decision makers, who expect a higher E_2 value to be guaranteed from their information gathering process, become less search averse within the corresponding subset of goods, i.e. the area where the H function remains above the F one increases for relatively low x_1 realizations. As a result, decision makers would require relatively higher realizations from the first characteristic space in order to continue gathering information on the observed good. Such an effect can also be observed in the risk averse setting illustrated in Figure 2 together with the increase in search aversion relative to the linear risk neutral case, an effect already described in the previous sections of the thesis. Thus, as risk aversion increases, an increase in the information gathering continuation area follows. Other than that, the signal effects are identical to those observed in the risk neutral case.

¹The basic unsigaled case described in the previous section is denoted by ns.

Consider the r.c.e.s. described in Figures 12 and 16. The same effects on the optimal information gathering behavior of decision makers as those described in the previous subsection can be observed in these figures.² In this case, however, the main result derived from these simulations relates to the optimum number of signals that may be issued by a firm. Note that the incentives to continue gathering information on the first good observed decrease after two positive [and credible] signals are received. Moreover, this decrement is relative to both the one signal and the unsignaled settings. Thus, a firm may face a constraint on the number of positive signals that it may issue despite their credibility. Educational and [subjective] quality constraints, together with the bandwagon and lock-in effects emphasized by Geroski (2000), indicate that, if a firm is unable to guarantee minimum quality levels, stricter acceptance criteria will [optimally] arise among decision makers when considering the set of products offered by the firm.

7.3 Numerical simulations: diffusion and network effects: decision irreversibility

The simplest way to mitigate the effect triggered by the r.c.e.s. on the information gathering incentives of the good whose first characteristic has been

²The negative effect of E_2 on $F(x_1|rf)$, derived analytically in the previous section, can also be observed in these figures. Note how as the observed realizations of X_1 improve they manage to compensate for the initial negative shock on $F(x_1|rf)$.

observed is to assume search and market frictions large enough so as to prevent decision makers from returning to the goods observed previously once they have discarded them. In this case, if decision makers were to start gathering information on a new good, different from the one whose first characteristic has been observed, they would have to forego any information obtained. Hence, gathering information on a new good constitutes an irreversible decision. This type of constraint brings the model closer to the sequential search and choice processes defined in the operational research literature, where, once a product is rejected, it is no longer considered as part of the available choice set of decision makers, see Ulu and Smith (2009).

Consider, for example, the g.c.e.s. after one signal is observed. As already illustrated, decision irreversibility has no effect on the behavior of the $F(x_1|\theta = 1)$ function. The corresponding $H(x_1|\theta = 1)$ function would be given by the expected utility value derived from being able to observe one characteristic from the set of available goods

$$H(x_1|nr) \stackrel{def}{=} \int_{ce_1}^{x_1^M} \mu_1(y_1)(u_1(y_1) + E_{2|\theta=1})dy_1 + \int_{x_1^m}^{ce_1} \mu_1(y_1)(E_1 + E_{2|\theta=1})dy_1.$$

Note that the decision maker aims at observing a characteristic above ce_1 in the signaled market or choosing randomly within it otherwise, and is unable to secure a given [observed] x_1 value due to the irreversibility assumption and the unique observation she has left.

Abusing notation, the version of the one signal irreversible case defined

within the r.c.e.s. would be given by

$$H(x_1|nr) \stackrel{def}{=} \int_{ce_1}^{x_1^M} \mu_1(y_1)(u_1(y_1) + E_{2|\theta=1})dy_1$$

Figures 13 and 17 illustrate this function, denoted by $H(nr)$, for the one signal r.c.e.s..³ Clearly, sufficiently large search and market frictions may improve the ability of firms to introduce their products in a given market. A reference to the previously highlighted educational, quality and bandwagon constraints could be easily made to justify the existence of this type of frictions.

³The unsigaled and two signal cases, as well as the corresponding settings defined within the g.c.e.s., follow trivially.

Chapter 8

Demand Appendix

This section analyzes the effect that observing a positive signal has on the behavior of the expected search utilities of rational decision makers. Consider the $F(x_1)$ function in the first place. Intuitively, one may infer that the updated Bayesian density $\mu_2(x_2|\theta = 1)$ should lead to a higher expected utility value on the X_2 interval, i.e. $E_{(2|\theta=1)} \geq E_2$, which should, at the same time, result in the set $P^+(x_1|\theta = 1)$ shrinking relative to $P^+(x_1)$. In addition, the type of positive signal received implies that $\mu_2(x_2|\theta = 1) \geq \mu_2(x_2)$ over the newly defined interval $P^+(x_1|\theta = 1)$. Thus, receiving a positive signal leads to a stricter $P^+(x_1)$ interval displaying a larger probability mass than its presignal counterpart. The intuitive effect of the signal on the $F(x_1)$ function remains ambiguous.

Regarding the $H(x_1)$ function, note that the $Q^+(x_1)$ and $Q^-(x_1)$ intervals do not depend on E_2 and are therefore not affected by the signal. However,

the direct dependence of $H(x_1)$ on E_2 should lead to an upward shift of the function if the value of E_2 increases after the signal is received.

In order to verify the previous intuitive description a formal treatment of the signal effects on both the $F(x_1)$ and $H(x_1)$ functions is provided. The following definition and proposition, taken from Mas-Colell et al. (1995), are required for the subsequent analysis.

Definition A.1 [Definition 6.D.1 in Mas-Colell et al. (1995)] *The distribution $F(\cdot)$ first-order stochastically dominates $G(\cdot)$ if, for every nondecreasing function $u : \mathbb{R} \rightarrow \mathbb{R}$, we have*

$$\int u(x)dF(x) \geq \int u(x)dG(x).$$

Proposition A.1 [Proposition 6.D.1 in Mas-Colell et al. (1995)] *The distribution of monetary payoffs $F(\cdot)$ first-order stochastically dominates the distribution $G(\cdot)$ if and only if $F(x) \leq G(x)$ for every x .*

Therefore, given the updated definition of both the F and H functions

$$\begin{aligned} F(x_1|\theta = 1) &\stackrel{def}{=} \int_{P^+(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(u_1(x_1) + u_2(x_2))dx_2 + \\ &\int_{P^-(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(E_1 + E_{(2|\theta=1)})dx_2 \\ H(x_1|\theta = 1) &\stackrel{def}{=} \left[\int_{Q^+(x_1)} \mu_1(y_1)(u_1(y_1) + E_{(2|\theta=1)})dy_1 + \right. \\ &\left. \int_{Q^-(x_1)} \mu_1(y_1)(\max\{u_1(x_1), E_1\} + E_{(2|\theta=1)})dy_1 \right] \end{aligned}$$

and the corresponding $E_{(2|\theta=1)} = \int_{X_2} \mu_2(x_2|\theta = 1)u_2(x_2)dx_2$ value, the following propositions can be stated

Proposition A.2 $F(x_1|\theta = 1) \geq F(x_1)$.

Proposition A.3 $H(x_1|\theta = 1) \geq H(x_1)$.

whose respective proofs are presented below.

Proof of proposition A.2. We will make use of the following Lemmas to illustrate Proposition A.2.

Lemma A.1 $\mu_2(x_2|\theta = 1)$ *first-order stochastically dominates* $\mu_2(x_2)$.

Proof. Consider the basic learning model defined in the thesis. The decision maker, who is assumed to have a [subjective] uniform probability density function defined on X_2 , receives a signal halving the probability mass allocated to the lower half density values while reallocating the subtracted mass uniformly among the upper half ones. That is, the initial uniform density, the signal received and the corresponding Bayesian updating rule defining the learning process of the decision maker are respectively given by

$$\begin{aligned}\mu_2(x_2) &= \frac{1}{\beta - \alpha} \quad \text{if } x_2 \in [\alpha, \beta] \\ \pi(\theta|x_2) &= \begin{cases} \frac{3}{2(\beta-\alpha)} & \text{if } x_2 \in (\frac{\alpha+\beta}{2}, \beta] \\ \frac{1}{2(\beta-\alpha)} & \text{if } x_2 \in [\alpha, \frac{\alpha+\beta}{2}] \end{cases} \\ \mu_2(x_2|\theta = 1) &= \frac{\pi(\theta|x_2)\mu_2(x_2)}{\int_{X_2} \pi(\theta|x_2)\mu_2(x_2)dx_2}\end{aligned}$$

Thus, the following updated density results from applying Bayes' rule after receiving a signal

$$\mu_2(x_2|\theta = 1) = \begin{cases} \frac{\frac{3}{2(\beta-\alpha)^2}}{\frac{1}{(\beta-\alpha)}} = \frac{3}{2(\beta-\alpha)} & \text{if } x_2 \in (\frac{\alpha+\beta}{2}, \beta] \\ \frac{\frac{2(\beta-\alpha)^2}{1}}{(\beta-\alpha)} = \frac{1}{2(\beta-\alpha)} & \text{if } x_2 \in [\alpha, \frac{\alpha+\beta}{2}] \end{cases}$$

Clearly, x_2 variants situated on the upper half of the distribution are assigned $\int_{\frac{\alpha+\beta}{2}}^{\beta} \mu_2(x_2|\theta = 1)dx_2 = 3/4$ of the total density while those on the lower half are endowed with the remaining $\int_{\alpha}^{\frac{\alpha+\beta}{2}} \mu_2(x_2|\theta = 1)dx_2 = 1/4$.

In order to illustrate the first order stochastic dominance of $\mu_2(x_2|\theta = 1)$ over $\mu_2(x_2)$ it must be shown that $\int_{\alpha}^{\beta} \mu_2(x_2|\theta = 1)dx_2 < \int_{\alpha}^{\beta} \mu_2(x_2)dx_2$, for all $x_2 \in [\alpha, \beta]$. Therefore, the resulting distribution functions must be calculated and compared for both codomains within $[\alpha, \beta]$.

- (i) Consider first the $x_2 \in [\alpha, \frac{\alpha+\beta}{2}]$ codomain. Clearly, $\mu_2(x_2|\theta = 1)$ first order stochastically dominates $\mu_2(x_2)$ if and only if (Mas-Colell et al., 1995)

$$\int_{\alpha}^{\frac{\alpha+x}{2}} \mu_2(x_2)dx_2 = \frac{x-\alpha}{2(\beta-\alpha)} > \int_{\alpha}^{\frac{\alpha+x}{2}} \mu_2(x_2|\theta = 1)dx_2 = \frac{x-\alpha}{4(\beta-\alpha)}.$$

$\forall x \in [\alpha, \beta]$. This inequality is satisfied whenever $x > \alpha$. Thus, $\mu_2(x_2|\theta = 1)$ stochastically dominates $\mu_2(x_2)$ for every $x > \alpha$, that is, $\forall x_2 \in [\alpha, \frac{\alpha+\beta}{2}]$.

- (ii) Consider now the $x_2 \in [\frac{\alpha+\beta}{2}, \beta]$ codomain. Once again, $\mu_2(x_2|\theta = 1)$ first order stochastically dominates $\mu_2(x_2)$ if and only if

$$\int_{\frac{\alpha+\beta}{2}}^x \mu_2(x_2)dx_2 + \int_{\alpha}^{\frac{\alpha+\beta}{2}} \mu_2(x_2)dx_2 >$$

$$\int_{\frac{\alpha+\beta}{2}}^x \mu_2(x_2|\theta=1)dx_2 + \int_{\alpha}^{\frac{\alpha+\beta}{2}} \mu_2(x_2|\theta=1)dx_2$$

$\forall x \in [\frac{\alpha+\beta}{2}, \beta]$. In the case under consideration the above inequality corresponds to

$$\frac{2x - \alpha - \beta}{2(\beta - \alpha)} + \frac{\beta - \alpha}{2(\beta - \alpha)} > \frac{6x - 3\alpha - 3\beta}{4(\beta - \alpha)} + \frac{\beta - \alpha}{4(\beta - \alpha)}$$

which simplifies to

$$\frac{x - \alpha}{\beta - \alpha} > \frac{3x - 2\alpha - \beta}{2(\beta - \alpha)}.$$

This inequality is satisfied for every $\beta > x$, that is, $\forall x_2 \in [\frac{\alpha+\beta}{2}, \beta]$.

Therefore, $\mu_2(x_2|\theta=1)$ first-order stochastically dominates $\mu_2(x_2)$ for every $x_2 \in [\alpha, \beta]$. A similar proof can be used to illustrate the first-order stochastic dominance of $\mu_2(x_2|\theta=2)$ over $\mu_2(x_2|\theta=1)$. ■

Even though we have only verified the first-order stochastic dominance resulting from the signal for the uniform density case defined in the thesis, the analysis could be generalized to any other density function whose probability mass is redistributed to generate higher expected utilities, refer to Chapter 6 in Mas-Colell et al. (1995).

Lemma A.1 together with Definition A.1 imply directly that

Corollary A.1 $E_{(2|\theta=1)} \geq E_2$.

The signal received affects the $F(x_1)$ function both through the new induced value of E_2 and the updated $\mu_2(x_2|\theta=1)$ density. While the previous

corollary describes the effect that signal-induced changes in the $\mu_2(x_2)$ density have on expected utilities, the following one concentrates on the effect that changes in the E_2 value have on $F(x_1)$ for a given constant $\mu_2(x_2)$. If the latter effect is positive, then coupling a signal-based increment in E_2 with a first-order stochastic dominance spread on $\mu_2(x_2)$ would lead to an increase of the $F(x_1)$ function.

Lemma A.2 $\left. \frac{dF(x_1)}{dE_2} \right|_{\mu_2(x_2)} > 0, \forall x_1 \in X_1$, if and only if $P^-(x_1^M) \neq \emptyset$.

Proof. We start by expressing $F(x_1)$ as a function of E_2

$$F(x_1) \stackrel{def}{=} \int_{u_2^{-1}(E_1+E_2-u_1(x_1))}^{x_2^M} \mu_2(x_2)(u_1(x_1) + u_2(x_2))dx_2 + \int_{x_1^m}^{u_2^{-1}(E_1+E_2-u_1(x_1))} \mu_2(x_2)(E_1 + E_2)dx_2$$

Applying Leibnitz's rule to the above definition while keeping $\mu_2(x_2)$ fixed allows us to isolate the effect that changes in the E_2 value have on the $F(x_1)$ function.

$$\begin{aligned} \left. \frac{dF(x_1)}{dE_2} \right|_{\mu_2(x_2)} &= \\ \int_{u_2^{-1}(E_1+E_2-u_1(x_1))}^{x_2^M} \frac{\partial}{\partial E_2} [\mu_2(x_2)(u_1(x_1)+u_2(x_2))]dx_2 &+ [\mu_2(x_2^M)(u_1(x_1)+u_2(x_2^M))] \frac{dx_2^M}{dE_2} - \\ [\mu_2(u_2^{-1}(E_1+E_2-u_1(x_1)))(u_1(x_1)+u_2(u_2^{-1}(E_1+E_2-u_1(x_1))))] &\frac{d}{dE_2} [u_2^{-1}(E_1+E_2-u_1(x_1))] + \\ \int_{x_1^m}^{u_2^{-1}(E_1+E_2-u_1(x_1))} \mu_2(x_2)dx_2 &+ \\ [\mu_2(u_2^{-1}(E_1+E_2-u_1(x_1)))(E_1+E_2)] \frac{d}{dE_2} [u_2^{-1}(E_1+E_2-u_1(x_1))] &- [\mu_2(x_1^m)(E_1+E_2)] \frac{dx_1^m}{dE_2} = \end{aligned}$$

$$\begin{aligned}
& 0 + 0 - [\mu_2(u_2^{-1}(E_1 + E_2 - u_1(x_1)))(E_1 + E_2)] \frac{d}{dE_2} [u_2^{-1}(E_1 + E_2 - u_1(x_1))] + \\
& \int_{x_2^m}^{u_2^{-1}(E_1 + E_2 - u_1(x_1))} \mu_2(x_2) dx_2 + \\
& [\mu_2(u_2^{-1}(E_1 + E_2 - u_1(x_1)))(E_1 + E_2)] \frac{d}{dE_2} [u_2^{-1}(E_1 + E_2 - u_1(x_1))] - 0 = \\
& \int_{x_2^m}^{u_2^{-1}(E_1 + E_2 - u_1(x_1))} \mu_2(x_2) dx_2.
\end{aligned}$$

Therefore, increments in E_2 have a strictly positive effect on $F(x_1)$, $\forall x_1 \in X_1$, iff $P^-(x_1^M) \neq \emptyset$. \blacksquare

Corollary A.1 and Lemma A.2 imply that if $P^-(x_1^M) \neq \emptyset$ and the signal received leads to $E_{(2|\theta=1)} > E_2$, then $F(x_1|E_{(2|\theta=1)}) > F(x_1)$. This result together with Lemma A.1 provide the required conclusion, i.e. $F(x_1|\theta = 1) \geq F(x_1)$ for all x_1 values in X_1 . In particular, if either $E_{(2|\theta=1)} \geq E_2$ or $P^-(x_1^M) = \emptyset$, or both, then

$$\begin{aligned}
F(x_1|\theta = 1) &\stackrel{def}{=} \int_{P^+(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(u_1(x_1) + u_2(x_2)) dx_2 + \\
&\int_{P^-(x_1|\theta=1)} \mu_2(x_2|\theta = 1)(E_1 + E_{(2|\theta=1)}) dx_2 \geq \\
F(x_1|E_{(2|\theta=1)}) &\stackrel{def}{=} \int_{P^+(x_1|\theta=1)} \mu_2(x_2)(u_1(x_1) + u_2(x_2)) dx_2 + \\
&\int_{P^-(x_1|\theta=1)} \mu_2(x_2)(E_1 + E_{(2|\theta=1)}) dx_2 \geq \\
F(x_1) &\stackrel{def}{=} \int_{P^+(x_1)} \mu_2(x_2)(u_1(x_1) + u_2(x_2)) dx_2 + \int_{P^-(x_1)} \mu_2(x_2)(E_1 + E_2) dx_2. \quad \blacksquare
\end{aligned}$$

Proof of Proposition A.3. The result follows directly from Corollary A.1 and the fact that

$$\frac{dH(x_1)}{dE_2} = \int_{Q^+(x_1)} \mu_1(y_1) dy_1 + \int_{Q^-(x_1)} \mu_1(y_1) dy_1 = 1 > 0. \quad \blacksquare$$

Chapter 9

Technological transition: the basics

Given the behavior of the optimal threshold values identified in the previous demand section, a basic strategic structure can be defined to model the introduction of technologically superior products. In this case, the technological superiority of a set of products is reflected by its stochastically dominant distribution of X_2 characteristics. The information acquisition incentives of the decision maker are illustrated by her expected utilities, which, at the same time, define the revenues expected to be obtained by the firms. That is, given the available distribution of product characteristics that may be displayed by a firm, its expected revenues depend on its ability to provide the characteristics required by the decision maker.

In other words, decision makers would be reluctant to purchase an ob-

served good whose expected utility value is lower than the one delivered by the certainty equivalent good defined within the corresponding market. That is, if the characteristics observed after gathering both pieces of information do not deliver an expected utility higher than $E_1 + E_2$ in the unsignaled market or $E_1 + E_{2|\theta=1}$ in the signaled one, then decision makers should refrain from making any purchase. Consequently, the following proposition summarizes the first basic [technological] transition finding of the thesis

Proposition 9.0.1 *Firms will optimally signal the product with the lowest available quality when generating technological signal-induced monopolistic markets.*

Thus, the worst available version of a new technologically superior product will be used to generate the corresponding signal-induced monopolistic market. Signaling an improved version would trivially lead to lower expected revenues for the monopolistic firm, given identical production costs.

On the other hand, the ability of decision makers to resort to a randomly chosen good provides an explicit reference point against which markets may be compared when defining their corresponding search strategies, which provides us with an important simplifying assumption when presenting the results obtained. Therefore, we will be assuming a g.c.e.s. throughout the rest of the thesis, that is, the current section and the forthcoming supply-based one.

Consider a standard symmetric economic duopoly. The strategies available to each identical firm consist of either signaling the introduction of an

improved set of X_2 product characteristics, $1S$, or not signaling it, NS . Denote by $E[r(\mu_2(x_2))]_A$ the current expected revenue obtained by each firm if none of them signals and both must compete for decision makers with respect to threshold A , refer to Figures 1 and 2. Similarly, $E[r(\theta)]_B$ corresponds to the expected revenue obtained by a firm from unilaterally signaling and facing less search averse decision makers at threshold B .

The following definition divides the set of possible game theoretical scenarios in two main different categories.

Definition 9.0.2 *Signaling an enhanced set of characteristics is a technologically neutral strategy if $E_{(2|\theta=1)} = E_2$, and it is not technologically neutral if $E_{(2|\theta=1)} > E_2$.*

If signaling an enhanced set of characteristics is technologically neutral, then the expected revenues obtained by firms would be independent of their signaling strategies. In this case, all entrances composing the corresponding *Technological Transition* matrix would be, by definition, equal to $E[r(\mu_2(x_2))]_A$, and transition between technologies become purely random events. However, if signaling is not a technologically neutral strategy, then the resulting transition game between technologies would be given by

Basic Technological Transition Game

	1S	NS
1S	$(< E[r(\theta)]_B), (< E[r(\theta)]_B)$	$E[r(\theta)]_B, 0$
NS	$0, E[r(\theta)]_B$	$E[r(\mu_2(x_2))]_A, E[r(\mu_2(x_2))]_A$

Clearly, if both firms signal the improvement, they must compete for consumers in the corresponding market, leading to a strictly smaller expected payoff, denoted by $(< E[r(\theta)]_B)$, than in a monopolistic environment where only one firm has signaled the improvement. The following results are immediate.

Proposition 9.0.3 *If $E[r(\theta)]_B > E[r(\mu_2(x_2))]_A$ (resp. $E[r(\theta)]_B = E[r(\mu_2(x_2))]_A$), the technological transition game has a unique Nash equilibrium, where signaling is a strictly (resp. weakly) dominant strategy for both firms.*

Proposition 9.0.4 *If $E[r(\theta)]_B < E[r(\mu_2(x_2))]_A$, the technological transition game has two Nash equilibria in pure strategies, $(1S, 1S)$ and (NS, NS) .*

Proposition 9.0.5 *If $E[r(\theta)]_B < E[r(\mu_2(x_2))]_A$, the technological transition game has a mixed strategy equilibrium.*

The mixed strategy equilibrium is defined by the set of probability pairs $\{(P_i^*(1S), P_i^*(NS))\}_{i=1,2}$, given by the solutions to

$$\frac{(< E[r(\theta)]_B)}{E[r(\mu_2(x_2))]_A + (< E[r(\theta)]_B) - E[r(\theta)]_B} = P_i^*(NS)$$

$$\frac{E[r(\mu_2(x_2))]_A - E[r(\theta)]_B}{E[r(\mu_2(x_2))]_A + (< E[r(\theta)]_B) - E[r(\theta)]_B} = P_i^*(1S)$$

where $P_i(NS)$ is the probability that firm i , with $i = 1, 2$, does not signal the existence of a technologically superior product and $P_i(1S) = 1 - P_i(NS)$.

Corollary 9.0.6 *Technological transition takes place in mixed strategies if $P_i(1S) > P_i^*(1S)$, with $i = 1, 2$, while it does not if $P_i(1S) < P_i^*(1S)$.*

9.1 Basic transition analysis

The main purpose of this section has been to illustrate how even in an environment with perfectly rational decision makers, credible signals, and without consumption inertia or any other market frictions, firms do not necessarily have an incentive to trigger the transition between markets unless sufficiently high monopolistic rents are guaranteed, and that, even in this case, technological improvements do not necessarily lead to higher expected revenues for the firms introducing them.

Technological transition may be fostered through the introduction of perdurable technological monopolies that increase the $E[r(\theta)]_B$ payoff relative to $E[r(\mu_2(x_2))]_A$, as the standard economic literature suggests, see Tirole (1988). However, the adoption of technologically superior goods by decision makers would be subject to stricter selection criteria. That is, the existence of technological monopolistic rents may guarantee faster introduction but not faster adoption. On the other hand, if sufficiently perdurable technological monopolies cannot be guaranteed, i.e. $E[r(\theta)]_B < E[r(\mu_2(x_2))]_A$, transition does only occur in mixed strategies. In this case, $\frac{\partial P^*(1S)}{\partial E[r(\theta)]_B} < 0$, $\frac{\partial P^*(1S)}{\partial (< E[r(\theta)]_B)} < 0$ and $\frac{\partial P^*(1S)}{\partial E[r(\mu_2(x_2))]_A} > 0$, implying that an increase in either $E[r(\theta)]_B$ or ($< E[r(\theta)]_B$), or a decrease in $E[r(\mu_2(x_2))]_A$ would lead to a larger set of $P^*(1S)$ values for which signaling constitutes an equilibrium strategy.¹

¹It should be remarked that the introduction of technological monopolistic rents resulting in $E[r(\theta)]_B > E[r(\mu_2(x_2))]_A$ may lead to a standard prisoner's dilemma matrix

The same type of analysis can be performed and similar conclusions are reached when considering the possibility of firms sending more than one signal. The following section studies in detail the two signals case and all the possible subcases arising within such a setting, and sets the basis for developing scenarios based on further signaling capabilities.

if $(< E[r(\theta)]_B) < E[r(\mu_2(x_2))]_A$. In this case, there exists a unique Nash equilibrium in pure strategies where both firms signal the improvement even if a decrease in expected revenues results from following such a (dominant) strategy. An intuitively related result is obtained by Fatas-Villafranca and Saura-Bacaicoa (2004), who design a differential dynamic macroeconomic structure to identify technological diffusion patterns. These authors illustrate the spontaneous emergence of recession periods engendered during apparently prosperous situations. In other words, technological improvements do not necessarily imply higher revenues for the firms introducing them or lead to higher consumption levels, as is the case in the current setting.

Chapter 10

Technological transition: general analysis

This section illustrates the set of equilibria arising when more than one signal may be sent by firms. It allows for a simple generalization of the analysis introduced in the main text to an environment with multiple technological improvements available to be signaled. Even though we will constraint the analysis to the two signals' case, additional scenarios accounting for further signaling possibilities can be easily inferred from the theoretical settings developed below. Throughout this section the firm will be represented as the upper matrix player, while the rival will be defined by the left one.

Consider first the case where either one or two signals may be sent by a firm but the rival is constrained to send a maximum of one signal.

Technological Transition Game (AI)

	2S	1S
1S	0, $E[r(\theta)]_C$	$(< E[r(\theta)]_B)$, $(< E[r(\theta)]_B)$
NS	0, $E[r(\theta)]_C$	0, $E[r(\theta)]_B$

Clearly, the [weakly] dominant strategy of the rival consists of signaling. In this case, the strategy of the firm depends on the relative values of $(< E[r(\theta)]_B)$ and $E[r(\theta)]_C$. The former denotes the expected revenue obtained when both firms compete at B , while the latter refers to the monopolistic revenue derived from unilaterally signaling at C . Thus, even though an equilibrium with 1S is immediately guaranteed, an equilibrium with 2S requires $(< E[r(\theta)]_B) < E[r(\theta)]_C$, a condition that will appear repeatedly through the coming games.

Note, as a corollary, that if the rival does not have any technological improvement to signal and the firm has an incentive to become a sole monopolist, i.e. $E[r(\theta)]_B > E[r(\mu_2(x_2))]$, then only one signal will be sent by the firm, since signaling twice leads to $E[r(\theta)]_C < E[r(\theta)]_B$.¹ In this sense, consider the incentives of firms to signal when both of them have access to the same technological improvements and must decide how many signals, either one or two, to issue.

¹That is, as the number of signals sent by a firm increases, the expected revenues derived from remaining as the sole signaling monopolist in a technological niche market decrease.

Technological Transition Game (AII)

	2S	1S
2S	$(< E[r(\theta)]_C), (< E[r(\theta)]_C)$	$E[r(\theta)]_C, 0$
1S	$0, E[r(\theta)]_C$	$(< E[r(\theta)]_B), (< E[r(\theta)]_B)$

The strategic structure of this game is identical to the one of the game analyzed in Section 9. In particular, both firms will signal if $(< E[r(\theta)]_B) < E[r(\theta)]_C$, while reversing this inequality leads to two Nash equilibria in pure strategies, i.e. $(1S, 1S)$ and $(2S, 2S)$, and a mixed one.

Consider now the case where a firm must choose whether or not and how many signals to issue when the rival cannot reach its same amount of technological improvements. That is, if the rival is able to issue only one signal, should the firm send two signals if available, or may a not signaling equilibrium prevail?

Technological Transition Game (AIII)

	2S	1S	NS
1S	$0, E[r(\theta)]_C$	$(< E[r(\theta)]_B), (< E[r(\theta)]_B)$	$E[r(\theta)]_B, 0$
NS	$0, E[r(\theta)]_C$	$0, E[r(\theta)]_B$	$E[r(\mu_2(x_2))]_A, E[r(\mu_2(x_2))]_A$

The equilibrium structures of this and the following game are quite similar in terms of signaling incentives.

- (i) If $E[r(\theta)]_B > E[r(\mu_2(x_2))]_A$, then signaling is a [weakly] dominant strategy for the rival. Therefore, the firm sends at least one signal, with the final equilibrium depending on

[(*ia*)] ($< E[r(\theta)]_B > E[r(\theta)]_C$): the firm sends a unique signal and the equilibrium would be given by $(1S, 1S)$.

[(*ib*)] ($< E[r(\theta)]_B < E[r(\theta)]_C$): the firm sends two signals and the corresponding equilibrium would be $(2S, 1S)$.

(*ii*) If $E[r(\theta)]_B < E[r(\mu_2(x_2))]$, then we have a mixed equilibrium similar to the one defined in Section 9. In addition to the (NS, NS) and $(1S, 1S)$ equilibria illustrated in the main text, we must also account for both $(2S, \cdot)$ possibilities, where two signals are sent by the firm and none or one by the rival.

The technological transition enhancing incentives described in (*i*) and (*ii*) are identical to those presented in the main text. That is, favoring monopolistic payoffs via $E[r(\theta)]_B$ increases the probability of the rival signaling, an action that guarantees at least a 1S equilibrium. If monopolistic incentives are also provided for the firm via $E[r(\theta)]_C$, then an equilibrium with 2S will be promoted.

Finally, consider the general case where firms must decide whether or not and how many signals to issue when both of them have access to the same amount of technological improvements.

Technological Transition Game (AIV)

	2S	1S	NS
2S	$(< E[r(\theta)]_C, < E[r(\theta)]_C)$	$E[r(\theta)]_C, 0$	$E[r(\theta)]_C, 0$
1S	$0, E[r(\theta)]_C$	$(< E[r(\theta)]_B, < E[r(\theta)]_B)$	$E[r(\theta)]_B, 0$
NS	$0, E[r(\theta)]_C$	$0, E[r(\theta)]_B$	$E[r(\mu_2(x_2))]_A, E[r(\mu_2(x_2))]_A$

- (i) If $E[r(\theta)]_B > E[r(\mu_2(x_2))]_A$, then not signaling is a [weakly] dominated strategy for both firms. The final equilibrium depends on the relative values of $E[r(\theta)]_C$ and $(< E[r(\theta)]_B)$ as follows

[(ia)] $(< E[r(\theta)]_B) > E[r(\theta)]_C$: both firms face a mixed equilibrium identical to the one defined in the *Technological Transition Game (AII)*, with the corresponding pure equilibria given by $(1S, 1S)$ and $(2S, 2S)$.

[(ib)] $(< E[r(\theta)]_B) < E[r(\theta)]_C$: both firms send two signals and the equilibrium would be given by $(2S, 2S)$.

- (ii) If $E[r(\theta)]_B < E[r(\mu_2(x_2))]_A$, then we have a mixed equilibrium similar to the one defined in the *Technological Transition Game (AIII)*. The pure strategy Nash equilibria would be given by (NS, NS) and $(2S, 2S)$. In addition, depending on the relative value of the $E[r(\theta)]_C$ and $(< E[r(\theta)]_B)$ payoffs, we may have the following equilibria

[(ia)] $(< E[r(\theta)]_B) > E[r(\theta)]_C$: an additional pure strategy Nash equilibrium would be given by $(1S, 1S)$.

[(ib)] $(< E[r(\theta)]_B) < E[r(\theta)]_C$: an additional pure strategy Nash equilibrium would be given by $(2S, 1S)$.

Once again, the technological transition enhancing incentives described in (i) and (ii) are identical to those presented in [the previous game and] the main text. That is, favoring monopolistic payoffs via $E[r(\theta)]_B$ increases the signaling probability of both firms, an action guaranteeing at least a 1S equilibrium. Besides, if monopolistic incentives are provided for both firms via $E[r(\theta)]_C$, then an equilibrium with 2S could be easily attained in both the (i) and (ii) subcases.

We are now ready to study the supply side of the economic system and the subsequent equilibria that result from the corresponding general competitive equilibrium analysis.

Chapter 11

Supply: consumer myopia and technological transition

This section and the following one will start by introducing several numerical simulations that illustrate the behavior of the optimal threshold values as the number of signals received by decision makers indicating the existence of a technologically superior set of goods increases. These simulations maintain the very same characteristics defined within the previous demand sections but will be used to emphasize the properties of demand that become particularly important for the signaling strategies of firms. In the current section we will concentrate on the existence of myopic decision makers, while the next and final one will consider the ability of decision makers to reverse their information gathering processes between different markets.

In the current setting, Figure 18 illustrates the one and two signals cases,

denoted by 1s and 2s, respectively, and the evolution of the corresponding threshold values within a basic risk neutral scenario. Points C and B identify the threshold values defined by decision makers when gathering information on a set of goods located within the unsignaled and the one signal market, respectively. These threshold values will constitute the main reference points when defining Nash pre-commitment equilibria. However, when studying subgame perfect equilibria, we will allow perfect foresight decision makers to shift their information gathering processes between markets after gathering an observation from one of them.¹ In this case, the distinction between irreversible and guaranteed improvement processes becomes extremely important. As in the Nash pre-commitment setting, the threshold point B illustrates a guaranteed improvement over C . In addition, point A represents the irreversible case, where decision makers must forego the observation gathered in the unsignaled market when shifting to the signaled one. This constraint decreases the expected search utility of decision makers due to the observation lost when shifting takes place. As a result, the corresponding $H(x_1|nr)$ function remains below the guaranteed improvement one for all $x_1 > ce_1$ values. Clearly, the threshold point A results from comparing the expected utility derived from checking the second characteristic of the good observed in the unsignaled market with that obtained from checking the first characteristic of a good in the signaled one.

¹This will be done to account for consumption inertia and habits in the information gathering processes of perfect foresight decision makers.

Figure 19 illustrates the same environment as Figure 18 but within a risk averse setting, where the utilities with which decision makers are endowed have been shifted from basic linear functions to square roots.

11.1 Basic assumptions

Given the behavior of the optimal threshold values identified above, a basic strategic structure can be defined to model the introduction of technologically superior products by firms among which the decision maker may search and choose.

Consider a standard symmetric economic duopoly. The strategies available to each identical firm consist of either signaling the introduction of an improved X_2 product characteristic, S , or not signaling it, NS . The following temporal sequence will be assumed. There are three time periods, $t = 0, 1, 2$. Period zero takes place before the decision maker observes any characteristic, while the two pieces of information are respectively gathered by the decision maker in periods one and two. Signals can only be received during the first two periods. That is, firms only interact strategically by trying to affect the information gathering process of decision makers in periods zero and one.

The information acquisition incentives of decision makers are illustrated by their expected utilities, which, at the same time, define the revenues expected to be obtained by firms. That is, given the available distribution of product characteristics that may be displayed by a firm, its expected revenues depend on its ability to provide the characteristics required by the decision

maker.

Hence, the following *terminal condition* will be imposed on the information gathering process of decision makers: if the characteristics observed after gathering both pieces of information are not higher than $ce_1 + ce_2$, then the decision maker will reject any available random choice. This condition is imposed to avoid biasing the choices made by decision makers, as well as the corresponding strategies of firms, towards the signaled market. If we were not to impose it, and both information pieces gathered lead to an expected utility lower than $E_1 + E_2$, then a perfect foresight decision maker would be forced to choose randomly from the signaled market. This would provide the signaling firm with a distinct advantage independently of its available distribution of X_1 characteristics. Moreover, we would be forcing all decision makers to consume independently of the outcome resulting from their information gathering processes. Thus, we will assume that for decision makers to purchase a good it must provide them with an expected utility higher than $E_1 + E_2$.²

²Note that, from a formal perspective, this assumption could be considered when defining the corresponding $F(\cdot)$ and $H(\cdot)$ functions, which should be modified accordingly, as we illustrated in the g.c.e.s. versus r.c.e.s. section. However, apart from complicating the presentation considerably, this assumption does not alter the qualitative results obtained through the game theoretical analysis presented in this section. Moreover, the corresponding definitions of the $F(x_1)$ and $H(x_1)$ functions determine the expected payoffs received from searching within a given market. Hence, the ability of decision makers to resort to a randomly chosen good provides an explicit reference point against which markets may be

Assume, finally, for analytical simplicity and consistency purposes, that the distribution of characteristics on X_1 and X_2 available to each firm is defined by a standard uniform distribution.³

Similarly to Rahman and Loulou (2001), two types of strategic equilibrium will be analyzed, each based on a different information transmission structure. A *Nash pre-commitment equilibrium* will be defined when firms are unable to observe the decisions made by their rivals and must commit to their time zero signaling strategies. If *subgame perfection* is assumed, firms may wait to observe the signaling strategy of the rival in period one and then decide whether or not to signal before the decision maker gathers her first piece of information. In this case, the interim signaling decision of the rival would have to be anticipated and incorporated in the period zero strategies of firms.

11.2 Nash pre-commitment equilibrium

It should be noted that through the current section of the thesis and the following one, the notation defining the entries of the *Technological Transition* compared when defining the search strategy of decision makers.

³This assumption can be relaxed and generalized to allow for any probability function. The corresponding results can be easily analyzed within any of the game theoretical scenarios presented. Note, however, that the distribution of characteristics considered by the decision makers should be modified accordingly. Otherwise, the current thesis should be extended to account for cheap talk, credibility and reputation scenarios.

Matrices will be modified and adapted to provide a more intuitive characterization of the [equilibrium] payoffs based on the corresponding figures. Refer to Figures 18 and 19 and denote by $E[r(k)]$ the expected revenue obtained by each firm when both firms compete for decision makers within the $k = B, C$ optimal threshold framework. Similarly, $E[r(B|s)]$ and $E[r(C|ns)]$ correspond to the expected revenue obtained from unilaterally signaling or not doing so, respectively.

The technological transition matrix that results from the signaling strategies available to firms within a pre-commitment environment can be defined as follows

Technological Transition Matrix

	S	NS
S	$E[r(B)], E[r(B)]$	$E[r(B s)], E[r(C ns)]$
NS	$E[r(C ns)], E[r(B s)]$	$E[r(C)], E[r(C)]$

Intuition suggests that, if both firms signal the improvement, they must compete for decision makers in the corresponding market, leading to a strictly smaller expected payoff, $E[r(B)]$, than the one obtained in a monopolistic environment by the firm that has signaled the improvement, $E[r(B|s)]$. In the latter case, the firm not signaling the improvement, and receiving $E[r(C|ns)]$, would be expected to suffer a loss relative to the not signaling equilibrium payoff, $E[r(C)]$, as perfect foresight decision makers shift their information gathering process to the signaled market. However, and despite the induced

decrease in competition, unilaterally signaling leads to a stricter threshold continuation criterion being imposed by perfect foresight decision makers. Thus, the incentives of firms to signal a technological improvement should depend on the relative magnitude of both these effects on their expected revenues.

We analyze formally below the revenues that firms expect to obtain based on the different threshold values defining the optimal information gathering behavior of decision makers and the number of competitors existing in each particular market.

Denote by $P(f)$ the [subjective] probability assigned by a firm to the decision maker observing a characteristic from one of its goods when competing [for decision makers] with a rival. Within a basic duopoly scenario, the probability assigned by a firm to the decision maker observing a characteristic from one of the goods offered by the rival equals $P(r) = 1 - P(f)$. Given the numerical simulations presented in the previous section, the probability that the decision maker continues gathering information on the good whose first characteristic she has observed can be easily defined and calculated. Denote this probability by $g(k) = (x_1^M - k)/(x_1^M - x_1^m)$, for $k = A, B, C$.⁴ Similarly, the probability that the decision maker does not continue gathering information on the good whose first characteristic she has observed is given by $1 - g(k) = (k - x_1^m)/(x_1^M - x_1^m)$, for $k = A, B, C$.⁵

⁴Abusing notation, we refer to k as both an information gathering threshold value and its projection on the X_1 domain.

⁵We have assumed that both the firm and its rival have identical uniform distributions

The firm's expected revenue when two pieces of information are left to gather and firms compete with each other for decision makers at k , where $k = B, C$, is given by⁶

$$E[r(k)] = P(f)[g(k)r_1(k) + (1 - g(k))[P(f)g(ce_1)r]] + \\ P(r)[(1 - g(k))[P(f)g(ce_1)r]], \quad (\star)$$

where $r_1(k)$ represents the firm's expected revenue when one piece of information is left to gather and $x_1 > k$, with $k = A, B, C$. That is,

$$r_1(k) = h(P^+(x_1))r,$$

where $h(P^+(x_1))$ denotes the probability assigned by the firm to the decision maker observing $x_2 > ce_1 + ce_2 - x_1$ and r is the revenue obtained by the firm from the sale of its product.

When competing with a rival, firms face a probability $P(f)$ of having one of their goods' first characteristics observed by the decision maker. If this is the case, the probability of the decision maker observing a x_1 higher than the corresponding k value equals $g(k)$. After observing $x_1 > k$, the

of available characteristics defined on the X_1 and X_2 sets. Thus, both firms face the same continuation and rejection probabilities in both the signaled and unsignaled markets. Note, however, that allowing for varying distributions of available characteristics between firms would modify their expected payoffs and the resulting equilibria.

⁶The $k = A$ case will be defined within the subgame perfect equilibrium setting, since it is irrelevant within the current pre-commitment framework and requires further assumptions and explanations.

decision maker will observe a x_2 such that $x_1 + x_2 > ce_1 + ce_2$ with probability $h(P^+(x_1))$, and purchase the good, leading to a firm's revenue of r . However, if $x_1 + x_2 < ce_1 + ce_2$, the decision maker remains without any observation left to gather and, due to the terminal condition imposed, would not purchase any good, leading to a revenue of zero. On the other hand, if $x_1 < k$, an event taking place with probability $(1 - g(k))$, it has been assumed that the decision maker may observe a new first characteristic from the set of goods offered by any of the firms.⁷ In this case, if the decision maker observes her final first characteristic from one of the firm's goods, she will only purchase it if $x_1 > ce_1$, an event taking place with probability $g(ce_1)$, where $g(ce_1) =$

⁷There is not a particular formal reason to either impose such a constraint or not doing so. Search frictions or their absence, lock-in effects or preference for diversified information, and customer education or learning bounds [see Eng and Quaia (2009)], could all be respectively assumed to bias the information gathering process of decision makers in favor of the firm whose good's first characteristic has been observed or its rival. If the assumed constraint is not imposed, the firm's expected revenue when two pieces of information are left to gather and firms compete with each other for decision makers at k would be given by

$$E[r(k)]' = P(f)[g(k)r_1(k)] + P(r)[(1 - g(k))[g(ce_1)r]], \quad k = B, C.$$

The revenue loss that $E[r(k)]'$ imposes on a firm relative to $E[r(k)]$ equals $P(f)[(1 - g(k))[P(f)g(ce_1)r]]$, while gains are accounted for by $P(r)[(1 - g(k))[g(ce_1)r]][1 - P(f)]$. Therefore, losses would be higher than gains if $P(f) > P(r)$. In the current context, since both firms have been assumed identical in all respects, which implies that $P(f) = P(r)$, no change in expected revenues would result from imposing such a constraint.

$$(x_1^M - ce_1)/(x_1^M - x_1^m).^8$$

The second term on the right hand side of equation (\star) corresponds to the expected revenue of a firm when the decision maker gathers her first observation from one of the rival's goods. The firm will only be able to obtain a revenue if the decision maker observes a $x_1 < k$ characteristic from its rival's good and then chooses the firm to gather her final piece of information, observing a value of $x_1 > ce_1$.

Note, finally, that equation (\star) can be simplified and rewritten as follows

$$E[r(k)] = P(f)r[g(k)h(P^+(x_1)) + (1 - g(k))g(ce_1)], \quad k = B, C.$$

When defining the expected payoffs obtained by firms in a unilateral signaling scenario, we must explicitly account for the existence of both myopic and perfect foresight decision makers within the population of potential consumers. Hence, the expected payoff received by the unilaterally signaling firm would be given by

$$\begin{aligned} E[r(B|s)] &= \alpha P(f)r[g(C)h(P^+(x_1)) + (1 - g(C))g(ce_1)] + \\ &\quad (1 - \alpha)r[g(B)h(P^+(x_1)) + (1 - g(B))g(ce_1)], \end{aligned}$$

where α denotes the proportion of myopic decision makers in the population. Note that perfect foresight decision makers will limit their search to the

⁸The $x_1 = k$ case can be included within any of the ones described in the main text. Note, however, that in the current continuous setting this event takes place with a probability of zero.

signaled market when gathering both of their available observations.⁹ Thus, if only one firm signals, it will compete with the not signaling firm for the α proportion of myopic decision makers in terms of threshold C while serving alone the $(1 - \alpha)$ perfect foresight proportion with respect to threshold B . The expected payoff obtained by the not signaling firm is therefore given by

$$E[r(C|ns)] = \alpha E[r(C)].$$

Clearly, $E[r(B|s)] > E[r(B)]$ when $\alpha = 0$ and $E[r(C|ns)] < E[r(C)]$ when $\alpha < 1$. However, comparisons between $E[r(B)]$ and $E[r(C)]$ depend on the relative values of the cumulative probabilities $h(P^+(x_1))$ and $g(ce_1)$. That is, assuming a set of threshold values that are sufficiently smooth so as to move in a continuous manner as signals are observed, we have

$$\frac{\partial E[r(k)]}{\partial k} = P(f)rg'(k)[h(P^+(x_1)) - g(ce_1)]$$

with $g'(k) < 0$. Given the assumptions introduced regarding the sets of characteristics, consider the value $\underline{x}_1 \in X_1$ that solves the following equation

$$u_1(\underline{x}_1) + u_2(x_2^M) = E_1 + E_2.$$

⁹We will relax this assumption when studying the subgame perfect equilibrium version of the game, where consumption habits and inertia will be allowed for among perfect foresight decision makers. In other words, while recognizing the technological superiority of the signaled set of goods, perfect foresight decision makers may still gather their observations from the unsignaled market due to persisting habits and inertia in consumption. It should however be emphasized that the results obtained in the pre-commitment game remain qualitatively unchanged by this assumption.

Any realization of X_1 below \underline{x}_1 prevents the decision maker from finding a good that delivers at least as much utility as the certainty equivalent one. Thus, $h(P^+(x_1)) = 0$ for all $x_1 < \underline{x}_1$. Conversely, as we move above \underline{x}_1 we will be losing combinations of X_1 and X_2 realizations that lead to an expected good strictly preferred to the certainty equivalent one.

Consider, for example, the case where the observed X_1 realization equals ce_1 . Note that we must have $x_2 > ce_2$ for the decision maker to purchase the good. Clearly, the probability that $x_2 > ce_2$ is lower than one, which implies that $h(P^+(x_1)) < g(ce_1)$ for $x_1 = ce_1$, leading to $\frac{\partial E[r(k)]}{\partial k} > 0$. Thus, in order for $\frac{\partial E[r(k)]}{\partial k} < 0$, i.e. for $h(P^+(x_1)) > g(ce_1)$, we must have $x_1 < ce_1$. Finally, note that if $h(P^+(\underline{x}_1)) < g(ce_1)$, then $\frac{\partial E[r(k)]}{\partial k} > 0$ for all k values.¹⁰

11.2.1 Myopic decision makers

If *all* decision makers are myopic, then the expected revenues obtained by firms would be independent of their signaling strategies. In this case, all entries composing the corresponding *Technological Transition Matrix* would be, by definition, equal to $E[r(C)]$, and transitions between technologies become purely random events, leading to identical Nash and subgame perfect equilibria.

¹⁰Given the uniform probability densities assumed, we have

$$h(P^+(\underline{x}_1)) = \int_{\underline{x}_1}^{x_1^M} \left(\frac{1}{x_1^M - x_1^m} \right) \left(\frac{x_2^M - x_2^*}{x_2^M - x_2^m} \right) dx_1$$

where $u_2(x_2^*) = E_1 + E_2 - u_1(x_1)$, for $x_1 \in [\underline{x}_1, x_1^M]$.

In addition, if, as suggested by Malerba et al. (2003), signaling the existence of a technologically superior good leads to frictions [i.e. in the form of lower quality as the product is initially introduced] decreasing the expected utility that [myopic] decision makers derive from the product, signaling firms would be unable to nurture a market niche where to survive and will disappear from the market.

Proposition 11.2.1 *If all decision makers are myopic and frictions exist within the signaled market, no technological transition takes place either under Nash pre-commitment or subgame perfection.*

Proof. Consider the technological transition matrix defined within a purely myopic setting. If, due to the induced frictions, signaling leads to a strictly lower payoff than $E[r(C)]$, then NS becomes a strictly dominant strategy for both firms. ■

11.2.2 Perfect foresight

As we already showed in the previous technological transition sections, if *all* decision makers have perfect foresight, i.e. if $\alpha = 0$ and $E[r(C|ns)] = 0$, the set of pre-commitment Nash equilibria will be defined by the relative values of $E[r(C)]$ and $E[r(B|s)]$. Consider first the scenario where $E[r(B|s)] > E[r(C)]$. In this case, signaling in period zero constitutes the unique pre-commitment Nash equilibrium.¹¹

¹¹Note that the pre-commitment Nash setting corresponds to that of a standard prisoner's dilemma if $E[r(B)] < E[r(C)]$. We restate here the main results presented through

Proposition 11.2.2 *If all decision makers have perfect foresight and $E[r(B|s)] > E[r(C)]$, then signaling is optimal independently of the relative values taken by $E[r(B)]$ and $E[r(C)]$.*

Similarly, signaling becomes a weakly dominant strategy if $E[r(B|s)] = E[r(C)]$. However, $E[r(B|s)] < E[r(C)]$ leads to a mixed pre-commitment Nash equilibrium based on the relative values of the matrix entries.

Proposition 11.2.3 *If all decision makers have perfect foresight and $E[r(B|s)] < E[r(C)]$, the technological transition game has two pre-commitment Nash equilibria, (S, S) and (NS, NS) , in pure strategies.*

Corollary 11.2.4 *If all decision makers have perfect foresight and $E[r(B|s)] < E[r(C)]$, the technological transition game has a [nondegenerate] mixed strategy equilibrium defined by*

$$\frac{E[r(C)] - E[r(B|s)]}{E[r(C)] + E[r(B)] - E[r(B|s)]} = P^*(S),$$

where $P^*(S)$ is the probability that a given firm signals the existence of a technologically superior good and $P^*(NS) = 1 - P^*(S)$.

Clearly, $\frac{\partial P^*(S)}{\partial E[r(B|s)]} < 0$ and $\frac{\partial P^*(S)}{\partial E[r(C)]} > 0$, implying that either an increase in $E[r(B|s)]$ or a decrease in $E[r(C)]$ would lead to a larger set of $P^*(S)$ values for which signaling constitutes an equilibrium strategy.

the technological transition sections in order to allow for basic direct comparisons between the [set of] equilibria derived from perfect foresight and myopic decision-based scenarios.

11.2.3 Myopic decision makers and perfect foresight

When both types of decision makers coexist in the market, the signaling firm would get all the perfect foresight consumers plus a share of the myopic ones, as defined by $E[r(B|s)]$ for $\alpha \in (0, 1)$. At the same time, the not signaling firm would receive an expected payoff of $\alpha E[r(C)] > 0$. Thus, the set of pre-commitment Nash equilibria depends on the relative values of $E[r(C)]$, $E[r(B)]$ and $E[r(B|s)]$.¹²

It should be emphasized that, in addition to the set of pre-commitment Nash equilibria defined for the perfect foresight case, the current framework allows for the existence of niche markets where only one of the firms signals the existence of a technologically superior good.

Proposition 11.2.5 *If the market consists of both perfect foresight and myopic decision makers, $E[r(B|s)] > E[r(C)]$ and $E[r(B)] < E[r(C|ns)]$, the technological transition game has two pre-commitment Nash equilibria, (S, NS) and (NS, S) , in pure strategies.*

The existence of these equilibria requires that $E[r(B|s)] > E[r(C)] > E[r(C|ns)] > E[r(B)]$. Such a string of inequalities can be guaranteed as-

¹²Note that, in this setting, $E[r(B|s)]$ is not based on all decision makers shifting their information gathering process to the signaled market, but only a $(1 - \alpha)$ proportion of them. Thus, if the signaled market were to provide a relative advantage over the unsignaled one for the signaling firm, i.e. $E[r(B)] > E[r(C)]$, the incentives to signal would be smaller than in the perfect foresight case.

suming both a value of α sufficiently close to zero and a large enough difference in payoffs between $E[r(B|s)]$ and $E[r(B)]$ via $(1 - P(f))$. These conditions translate into requiring that a relatively low proportion of myopic decision makers exists in the market and that sufficiently large monopolistic rents are obtained from unilaterally signaling when compared to competing in the signaled market. It is indeed the strength of the $(1 - P(f))$ effect what would guarantee that $E[r(B|s)]$ is higher than both $E[r(C)]$ and $E[r(B)]$.

Note that, as was the case in the perfect foresight scenario, a relatively high $E[r(B|s)]$ payoff provides firms with a strong incentive to signal the existence of a technologically superior product. In this case, both firms will try to be the first one to signal, as if they were competing on a technological race where the winner enjoys the monopolistic rents reflected by the $E[r(B|s)] > E[r(C|ns)]$ inequality.

Finally, it should be emphasized that the previous analysis could be extended to study the existence of correlated equilibria and the conditions for the creation of niche market within the current setting. However, we will be dealing with this type of results in the following section, where more natural conditions for the coordinated generation of niche market emerge.

11.3 Subgame perfection

We identify now the set of possible subgame perfect equilibria, which will be based on the relative matrix entry values achieved at each signaling time

period. Consider first the technological transition matrices that may be faced by firms in period one, just before decision makers start gathering information.

Guaranteed Improvement Technological Transition Matrix Period One

	S	NS
S	$E[r(B)], E[r(B)]$	$E[r(B s)], E[r(C ns)]$
NS	$E[r(C ns)], E[r(B s)]$	$E[r(C)], E[r(C)]$

Irreversibility Technological Transition Matrix Period One

	S	NS
S	$E[r(B)], E[r(B)]$	$E[r(A - C s)], E[r(C - A ns)]$
NS	$E[r(C - A ns)], E[r(A - C s)]$	$E[r(C)], E[r(C)]$

The strategies of the firm are described in the upper row, while the left column corresponds to those of the rival. Both types of decision reversibility processes can be explicitly differentiated through the (S, NS) and (NS, S) entries of their respective matrices. In this regard, the former matrix refers to the guaranteed improvement setting while the latter stands for the decision irreversibility one.

Clearly, the *guaranteed improvement* setting highly resembles the Nash pre-commitment one. Indeed, its set of equilibria will be determined by the relative values of $E[r(B)], E[r(C)], E[r(B|s)]$, and that of the α proportion of myopic decision makers. However, subgame perfection allows firms to

coordinate the creation of niche markets in the interim period after observing the signaling strategy of the rival, a task significantly harder to achieve in the pre-commitment case.

The set of outcomes derived from the *decision irreversibility* setting is slightly more cumbersome. We have denoted by $E[r(A - C|s)]$ the expected payoff received by the signaling firm when only one of them signals and decisions are irreversible, i.e. the decision maker foregoes the x_1 characteristic observed in the unsignaled market when moving to the signaled one. In this case, the payoff received by the not signaling firm has been denoted by $E[r(C - A|ns)]$. Both these payoffs will be explicitly defined to capture consumption inertia in the information gathering process of decision makers. That is, as emphasized by Malerba et al. (2003), the introduction of a new product within a given industry relies on the existence of experimental consumers that may allow for its survival through the creation of specialized niche markets. In the current setting, such an assumption implies that despite the technological superiority of the set of signaled goods, even perfect foresight decision makers may be reluctant to initially shift their information gathering processes to the signaled market.¹³ As a result, perfect foresight decision makers could still gather their first observation from the unsignaled market and shifting may take place afterwards.

¹³The existence of network effects could also provide the required intuition, as it is always challenging for decision makers to be among the first consumers of a new technology while abandoning an already established one.

Consider the unilateral signaling scenario from the perspective of the not signaling firm and define its expected payoff by

$$E[r(C-A|ns)] = (1-\alpha)\{P(f)[g(A)r_1(A)]+P(r)[(1-g(B))P(f)g(A)r]\}+\alpha E[(C)]$$

If a [perfect foresight] decision maker gathers her first observation from the [set of goods offered by the] not signaling firm and it is lower than A , an event happening with probability $P(f)(1 - g(A))$, then she will shift to the signaled market in order to gather her last observation, leading to a payoff of zero for the not signaling firm. For consistency purposes, the second right hand side term of the equation requires the last x_1 gathered from the unsignaled market to be above A for the decision maker to choose the corresponding good and nothing otherwise.¹⁴ A similar analysis could be performed to describe $E[r(A - C|s)]$, where

$$\begin{aligned} E[r(A - C|s)] = \\ (1-\alpha)\{P(f)[g(B)r_1(B)+(1-g(B))P(f)g(ce_1)r]+P(r)[(1-g(A))g(ce_1)r]\}+ \\ \alpha E[(C)]. \end{aligned}$$

There exists a substantial difference between the assumptions underlying $E[r(A - C|s)]$ and those used to define $E[r(k)]$, with $k = B, C$. In both $E[r(k)]$ cases, if the decision maker observed a $x_1 < k$ characteristic from

¹⁴Note, however, that even if we take ce_1 as the main reference point instead of A , $E[r(C - A|ns)] < E[r(B)]$ for $\alpha = 0$, as is required in the following subsection to define the perfect foresight subgame equilibria.

a firm's good, it was assumed that she could start gathering her second information piece from any of the two firms. In the current setting, *perfect foresight* decision makers are not indifferent between both markets if $x_1 < A$ in the unsignaled one. That is, once the initial inertia is overcome, decision makers will shift their information gathering process to the signaled market if $x_1 < A$ in the unsignaled one. However, if $x_1 < B$ in the signaled market, it has been assumed that perfect foresight decision makers may still gather their last piece of information from the signaled market with probability $P(f)$. These assumptions have been imposed to reflect the preference for experimentation that perfect foresight [experimental] decision makers must exhibit after becoming aware of the existence of technologically superior products and despite the initial consumption inertia they may be subject to.

11.3.1 Perfect foresight

Given the set of expected payoffs defined above, three possible technological transition matrices with their corresponding equilibria could be defined in period zero.

If $E[r(C)]$ is higher than $E[r(B|s)]$ and $E[r(A - C|s)]$, then a not signaling strategy from the firm in period zero implies that the rival will not signal in period one. In the same way, $\alpha = 0$ implies that $E[r(C|ns)] = 0$ and $E[r(C - A|ns)] < E[r(B)]$, which leads to

Technological Transition Matrix Period Zero

	S	NS
S	$E[r(B)], E[r(B)]$	
NS		$E[r(C)], E[r(C)]$

The subgame perfect equilibrium depends on the relative values of $E[r(B)]$ and $E[r(C)]$. In this case, both firms will coordinate their strategies in equilibrium by either signaling or not the existence of a technologically improved set of goods.

In the guaranteed improvement case, if $E[r(B|s)] > E[r(C)]$, then a not signaling strategy from the firm in period zero implies that the rival will signal in period one, leading to

Technological Transition Matrix Period Zero

	S	NS
S	$E[r(B)], E[r(B)]$	$E[r(B s)], 0$
NS		

Clearly, the subgame perfect equilibrium consists of both the firm and its rival signaling the existence of an improved technology in period zero.

In the irreversible case, if $E[r(A - C|s)] > E[r(C)]$, then a not signaling strategy from the firm in period zero implies that the rival will signal in period one, leading to

Technological Transition Matrix Period Zero

	S	NS
S	$E[r(B)], E[r(B)]$	$E[r(A - C s)], E[r(C - A ns)]$
NS		

The subgame perfect equilibrium depends on the relative values of $E[r(B)]$ and $E[r(C - A|ns)]$. Given the assumptions imposed when defining $E[r(C - A|ns)]$ and the fact that $g(A) < g(B)$, it can be easily shown that $E[r(C - A|ns)] < E[r(B)]$, making of signaling an equilibrium strategy for the firm.¹⁵

The following results are immediate.

Proposition 11.3.1 *If all decision makers have perfect foresight, $E[r(B|s)] < E[r(C)]$ and $E[r(A - C|s)] < E[r(C)]$, the technological transition game has a unique subgame perfect equilibria, (NS, NS) .*

Proof. If all decision makers have perfect foresight, $E[r(B|s)] < E[r(C)]$ and $E[r(A - C|s)] < E[r(C)]$, then not signaling is a dominant strategy for both firms if $E[r(B)] < E[r(C)]$. This is indeed the case since $E[r(B|s)] > E[r(B)]$ and $E[r(A - C|s)] > E[r(B)]$ when $\alpha = 0$. Thus, $E[r(C)] > E[r(B)]$, and not signaling constitutes the unique subgame perfect equilibrium. ■

¹⁵However, if our assumptions are modified, in particular those regarding preference for experimentation, not signaling may become an optimal strategy, leading to the creation of niche markets signaled by the rival.

Proposition 11.3.2 *If all decision makers have perfect foresight, $E[r(B|s)] > E[r(C)]$ and $E[r(A - C|s)] > E[r(C)]$, the technological transition game has a unique subgame perfect equilibrium where both firms signal.*

Note that, as in the Nash pre-commitment case, niche markets are *not* generated when all decision makers have perfect foresight. The technological transition either takes place or not, based on the expected payoffs derived from unilaterally signaling, i.e. $E[r(B|s)]$ and $E[r(A - C|s)]$. Such a result is due to the zero payoff received by the firms that do not signal when the rival does, which, at the same time, is due to the absence of myopic decision makers in the market.

11.3.2 Myopic decision makers and perfect foresight

We have just illustrated how the existence of perfect foresight decision makers helps triggering the transition towards the signaled market by penalizing those firms that do not signal when an incentive to unilaterally doing so exists. Consequently, the coexistence of both types of decision makers in the market will constraint such a tendency [but also allow for the creation of niche markets where innovative signaling firms may survive].

It should be noted that the set of equilibria obtained in the previous subsection could also be generated in the current one. However, we will concentrate here on highlighting the conditions required for the creation of niche markets where signaling firms may survive and comparing the resulting

equilibria with those introduced in the pre-commitment and perfect foresight cases.

In the guaranteed improvement case, if $E[r(B)] < E[r(C|ns)]$, then a signaling strategy from the firm in period zero implies that the rival will not signal in period one.¹⁶ Besides, **if $E[r(C)]$ is lower than $E[r(B|s)]$,** then a not signaling strategy from the firm in period zero implies that the rival will signal in period one. The period zero matrix would be given by

Technological Transition Matrix Period Zero

	S	NS
S		$E[r(B s)], E[r(C ns)]$
NS	$E[r(C ns)], E[r(B s)]$	

As in the corresponding Nash pre-commitment case, the existence of niche equilibria requires both $E[r(B)] < E[r(C|ns)]$ and $E[r(C)] < E[r(B|s)]$. It follows that $E[r(B)] < E[r(C|ns)] < E[r(C)] < E[r(B|s)]$. In this case, since $E[r(C|ns)] < E[r(B|s)]$, the firm has a clear incentive to be the first one to signal and let the rival follow a not signaling strategy.

In the irreversible case, if $E[r(A - C|s)] > E[r(C)]$, then a not signaling strategy from the firm in period zero implies that the rival will signal in period one. Besides, **if $E[(C - A|ns)]$ is higher than $E[(B)]$,** then a signaling strategy from the firm in period zero implies that the rival will not

¹⁶Note that this payoff inequality is possible since $\alpha > 0$, implying that $E[r(C|ns)] > 0$.

signal in period one.¹⁷ The period zero matrix would be defined as follows

Technological Transition Matrix Period Zero

	S	NS
S		$E[r(A - C s)], E[r(C - A ns)]$
NS	$E[r(C - A ns)], E[r(A - C s)]$	

Given the assumptions imposed when defining $E[r(C - A|ns)]$ and the fact that $g(A) < g(B)$, it can be easily shown that $E[r(A - C|s)] > E[r(C - A|ns)]$, making of signaling an optimal period zero strategy for a firm. Thus, as in the guaranteed improvement case, a firm has a clear incentive to be the first one to signal in period zero while letting the rival follow a complementary not signaling strategy in period one. If the firm does not signal in period zero, the rival will, generating a niche specialized market for developed technological goods.

Note that in the current setting $E[r(A - C|s)]$ is higher than both $E[r(B)]$ and $E[r(C)]$. That is, firms obtain the highest possible expected payoff by becoming sole monopolists within the niche signaled markets. The requirements imposed to reach this equilibrium provide us with the following intuition

- (i) In order for $E[r(C - A|ns)] > E[r(B)]$ we must have both $E[r(C)] > E[r(B)]$ and a sufficiently high value of α , since $E[r(C - A|ns)] <$

¹⁷As in the guaranteed improvement case, this payoff inequality is possible due to the $\alpha > 0$ assumption.

$E[r(B)]$ when $\alpha = 0$. Therefore, the not signaling firm remains as a follower of the signaled market monopolist if a relatively large proportion of myopic decision makers exists in the market and competing in the signaled market constitutes a loss with respect to the corresponding expected payoff obtained in the unsignaled one.

- (ii) In order for $E[r(A-C|s)] > E[r(C)]$ the effect of $P(r)[(1-g(A))g(ce_1)r]$ has to compensate (against $P(r)[(1-g(C))P(f)g(ce_1)r]$) for the relative loss induced by $P(f)[g(B)r_1(B) + (1-g(B))P(f)g(ce_1)r]$, which is due to the $E[r(C)] > E[r(B)]$ requirement. That is, the relative loss that results from competing in the signaled market, as opposed to the unsignaled one, must be compensated by the gain derived from the lesser ability of the rival to provide decision makers with a x_1 characteristic above A when compared to point C .

The following results are immediate.

Proposition 11.3.3 *If both types of decision makers coexist in the market, improvement is guaranteed, $E[r(B)] < E[r(C|ns)]$ and $E[r(C)] < E[r(B|s)]$, the technological transition game has a subgame perfect equilibrium leading to the creation of a signaling niche market.*

Corollary 11.3.4 *If both types of decision makers coexist in the market, improvement is guaranteed, $E[r(B)] < E[r(C|ns)]$ and $E[r(C)] < E[r(B|s)]$, both firms have an incentive to be the first one to signal and dominate the technological niche market under subgame perfection.*

Proposition 11.3.5 *If both types of decision makers coexist in the market, decisions are irreversible, $E[r(C)] < E[r(A - C|s)]$ and $E[r(B)] < E[r(C - A|ns)]$, the technological transition game has a subgame perfect equilibrium leading to the creation of a signaling niche market.*

Corollary 11.3.6 *If both types of decision makers coexist in the market, decisions are irreversible, $E[r(C)] < E[r(A - C|s)]$ and $E[r(B)] < E[r(C - A|ns)]$, both firms have an incentive to be the first one to signal and dominate the technological niche market under subgame perfection.*

Note that the incentives for the generation of market niches are identical in both the guaranteed improvement and irreversible settings. In this sense, the importance of the monopolistic rents derived from unilaterally signaling is reflected by $E[r(C)] < E[r(B|s)]$ and $E[r(C)] < E[r(A - C|s)]$, respectively. In addition, the incentives not to trigger additional competition in the niche market once a firm has signaled are respectively provided by $E[r(B)] < E[r(C|ns)]$ and $E[r(B)] < E[r(C - A|ns)]$.

However, a small difference between both setting exists. In the guaranteed improvement scenario, monopolistic rents provide firms with a signaling incentive that dominates all other possible payoffs, i.e. $E[(B)] < E[(C|ns)] < E[(C)] < E[(B|s)]$. In this case, the status quo payoff defined by $E[r(C)]$ constrains the joint introduction of superior technological products and it is the existence of monopolistic rents from unilaterally signaling what promotes their introduction through niche markets. As in the Nash pre-commitment

case, the incentives to signal are provided by low enough α and sufficiently large $(1 - P(f))$ values. In the irreversible scenario, a similar type of reasoning would require $E[r(C)] > E[r(C - A|ns)]$,¹⁸ an inequality that cannot be guaranteed analytically.

¹⁸For this to be the case, it would suffice to assume that $(1 - g(C)) > P(r)(1 - g(B))$.

Chapter 12

Supply: decision reversibility and technological transition

Consider the numerical representations of the three types of decision processes defined within the *Climbing the Quality Ladder* subsection 4.1, which are illustrated in Figures 20 and 21. In both figures the unsignaled market is represented by the $F(ns)$ and $H(ns)$ functions and decision makers receive a credible signal indicating the existence of a set of technologically superior products.

The guaranteed improvement case, denoted by $H(fg)$, allows for an immediate transition to the signaled market among decision makers independently of the value of the x_1 observation gathered in the unsignaled market, since $H(fg) > F(ns)$, $\forall x_1 \in X_1$. Clearly, this type of result cannot be generated by either the irreversible or the reversible decision processes, denoted by

$H(nr)$ and $H(r)$, respectively. While decision irreversibility may be expected to impose a large constraint on the information gathering process of decision makers, decision reversibility should be expected to allow for more flexibility when defining the transition between markets.¹ Note, however, that for the effects of market reversibility to become evident, the x_1 required to be observed in the unsignaled market must be relatively high. This phenomenon is exacerbated in the risk averse case, as Figure 21 shows, where the utilities with which decision makers are endowed have been transformed from basic linear functions to square roots. Note also, that in both the risk averse and neutral cases the slope of $H(r)$ is considerably smaller than that of $H(fg)$ through their respective upward sloping regions. Clearly, the ability of signaling firms to guarantee the x_1 value observed in the unsignaled market but a $E_{2|\theta=1} > E_2$ is responsible for this type of effect.

Thus, depending on the type of stochastic improvement defined, one signal may not suffice to differentiate the threshold continuation regions defined by reversible and irreversible decision processes.² In any case, the stochastic

¹The intuition for this assertion follows from the decrease in the expected search utility of decision makers due to the observation lost in the irreversible case when shifting between markets takes place. As a result, the corresponding $H(nr)$ function remains below the guaranteed improvement one for all $x_1 > ce_1$ values.

²Indeed, a relatively small stochastic improvement may lead to identical threshold values lower than ce_1 being defined for both decision processes. In this case, the analysis presented in the game theoretical [supply] section should be modified, since both decision processes would lead to the same expected revenue function, i.e. the reversibility effect vanishes for threshold continuation values lower than ce_1 . A similar, but more complex,

improvement defined in Section 4 will allow us to differentiate the expected payoffs obtained by firms for all types of decision processes and will therefore be maintained through the rest of the thesis.

In order to simplify the presentation, Figures 18 and 19 illustrate only the guaranteed improvement and irreversible decision processes, since the latter shares the information gathering threshold with the reversible case. Figure 18 illustrates the one and two signals cases, denoted by 1s and 2s, respectively, and the evolution of the corresponding threshold values within a basic risk neutral scenario. Points C and B identify the threshold values defined by decision makers when gathering information on a set of goods located within the unsignaled and the one signal market, respectively. Threshold point B illustrates a guaranteed improvement over C , while point A represents both the irreversible and reversible cases. Clearly, threshold point A results from comparing the expected utility derived from checking the second characteristic of the good observed in the unsignaled market, $F(ns)$, with that obtained from checking the first characteristic of a good in the signaled one, $H(nr)$. Figure 19 illustrates the same environment as Figure 18 but within a risk averse setting, where the utilities with which decision makers are endowed have been shifted once again from basic linear functions to square roots.

Clearly, as already stated in the previous sections, positive signals generation problem would also arise in the guaranteed improvement setting for small stochastic improvements. Note, in particular, that the slope of $H(fg)$ after ce_1 is higher than that of $F(ns)$, which would allow for multiple thresholds values.

ating first order stochastic dominant beliefs lead to higher expected utility levels for all possible x_1 values. However, in doing so, signals shift the respective optimal threshold values towards higher x_1 realizations in both markets. The intuition arising from these results states that positive signals should generate immediate herds of consumers towards the subset of goods on which they are defined, but, at the same time, decision makers, who expect a higher E_2 value to be guaranteed from their information gathering process, become less search averse within both markets. That is, the set of X_1 realizations for which the corresponding $H(x_1)$ function remains above $F(x_1)$ increases from $[x_1^m, C]$ to $[x_1^m, B]$ when shifting to the signaled market and from $[x_1^m, C]$ to $[x_1^m, A]$ if the decision maker remains within the unsignaled one. As a result, decision makers would require relatively higher realizations from the first characteristic space in order to continue gathering information on the observed good.

Such an effect can also be observed in the risk averse setting illustrated in Figure 19. Note, however, once again, the increase in search aversion relative to the linear risk neutral case. Other than that, the signal effects are identical to those observed in the risk neutral case.

12.1 Basic assumptions

Given the behavior of the optimal threshold values identified in the previous section, a basic strategic structure can be defined to model the introduction of technologically superior products by firms among which the decision maker

may search and choose.

We will repeat here several of the assumptions and environmental constraints that were introduced in the previous section on consumer myopia. This is done for comparability purposes. In the current setting, a reversibility property of the information gathering process of decision makers will be used to generate technological niche markets, as opposed to the existence of myopic decision makers introduced in the previous section. The notation will therefore be slightly different but the intuition basically the same. This will particularly be the case within the *Absence of niche markets* subsection, where the basic game theoretical equilibria presented in the previous section will be restated within a setting composed exclusively by perfect foresight decision makers. The most important changes will be introduced through the *Generating niche markets* subsection, where the reversibility of the information gathering processes of decision makers determines the equilibria of the corresponding set of technological transition games.

Consider a standard symmetric economic duopoly. The strategies available to each identical firm consist of either signaling the introduction of an improved X_2 product characteristic, S , or not signaling it, NS . The following temporal sequence will be assumed. There are three time periods, $t = 0, 1, 2$. Period zero takes place before the decision maker observes any characteristic, while the two pieces of information are respectively gathered by the decision maker in periods one and two. Signals can only be received during the first two periods. That is, firms only interact strategically by trying to affect the

information gathering process of decision makers in periods zero and one. Consequently, we will concentrate the analysis on *subgame perfect equilibria*, where firms may wait to observe the signaling strategy of the rival in period one and then decide whether or not to signal just before the decision maker gathers her first piece of information. In this case, the interim signaling decision of the rival has to be anticipated and incorporated in the period zero strategies of firms.

The information acquisition incentives of decision makers are illustrated by their expected utilities, which, at the same time, define the revenues expected to be obtained by firms. That is, given the available distribution of product characteristics that may be displayed by a firm, its expected revenues depend on its ability to provide the characteristics required by the decision maker.

Hence, the following *terminal condition* will be imposed on the information gathering process of decision makers: if the characteristics observed after gathering both pieces of information do not define goods whose expected utility is higher than $E_1 + E_2$, then the decision maker will reject any available random choice. This condition is imposed to avoid biasing the choices made by decision makers, as well as the corresponding strategies of firms, towards the signaled market. If we were not to impose it, and both information pieces gathered lead to goods with an expected utility lower than $E_1 + E_2$, then decision makers would be forced to choose randomly from the signaled market. This would provide the signaling firm with a distinct advantage in-

dependently of its available distribution of X_1 characteristics. Moreover, we would be forcing decision makers to consume independently of the outcome resulting from their information gathering processes. Thus, we will assume that for decision makers to purchase a good it must provide them with an expected utility higher than $E_1 + E_2$.³

Assuming that the technological improvements introduced by the signaling firm must be defined upon $E_1 + E_2$ instead of $E_1 + E_{2|\theta=1}$ imposes an important constraint on the model. In this sense, the analysis of the supply side presented in the thesis remains unchanged when *both firms* are subject to the same minimum quality constraints, i.e. both must improve upon either $E_1 + E_2$ or $E_1 + E_{2|\theta=1}$.

Due to the credibility of the signals and the basic dynamic structure of

³Note that, from a formal perspective and as emphasized in the previous section, this assumption could be considered when defining the $F(x_1)$ and $H(x_1)$ [together with the $H(x_1|nr)$, $H(x_1|fg)$ and $H(x_1|r)$] functions, which should be modified accordingly. However, even though imposing formally such a constraint does not significantly modify the results presented in the previous section, which were mainly based on the percentage of myopic decision makers existing in the economy, it would indeed alter the main results obtained within the current one, i.e. a reinterpretation of the model within a choice setting defined by discontinuous H functions would be required. We will not consider this alternative scenario in the current thesis, though it constitutes a plausible extension. Once again, the ability of decision makers to resort to a randomly chosen good provides an explicit reference point against which markets may be easily compared when defining the search strategy of decision makers. As a result, the simplified continuous version of the expected search utilities will be maintained.

quality ladders, we assume that improvements must take place upon the technological level displayed by the current set of unsigned goods, defining a $E_1 + E_2$ reference point for all decision makers.⁴ In this case, signaling constitutes an advantage due to the credibility of the signal, since $E_{2|\theta=1} > E_2$.⁵ However, one of the main points highlighted in the thesis is that, despite the relative advantage provided by a credible signal, the creation of niche markets may not be the best option available to the signaling firm.

Assume, finally, for analytical simplicity and consistency purposes, that the distribution of characteristics on X_1 and X_2 available to each firm is defined by a standard uniform distribution.

12.2 Game theoretical setting

We identify below the set of possible subgame perfect equilibria for both firms resulting from the demand-based strategic signaling environment. These equilibria will be based on the relative matrix entry values achieved at each

⁴This assumption becomes particularly important when defining the $h(P^+(x_1))$ function within the $r_1(k)$ expression later on. Imposing different certainty equivalent constraints for each market would complicate the presentation and oblige us to modify the analysis substantially. For example, inequalities such as $E_I[r(C - A|ns)] < E[r(B)]$, could not longer be guaranteed analytically. Thus, extensions of the current model should account for the effect that different reference points have both on the optimal behavior of decision makers and the signaling strategies of firms.

⁵The dual of this formulation would impose a disadvantage on the not signaling firm for the very same reason, with both firms being assumed to improve upon $E_1 + E_{2|\theta=1}$.

signaling time period.

Consider first the technological transition matrices that may be faced by firms in period one, just before decision makers start gathering information.

Guaranteed Improvement Technological Transition Matrix [Period One]

	S	NS
S	$E[r(B)], E[r(B)]$	$E[r(B s)], E[r(C ns)]$
NS	$E[r(C ns)], E[r(B s)]$	$E[r(C)], E[r(C)]$

Irreversible Technological Transition Matrix [Period One]

	S	NS
S	$E[r(B)], E[r(B)]$	$E_I[r(A - C s)], E_I[r(C - A ns)]$
NS	$E_I[r(C - A ns)], E_I[r(A - C s)]$	$E[r(C)], E[r(C)]$

Reversible Technological Transition Matrix [Period One]

	S	NS
S	$E[r(B)], E[r(B)]$	$E_R[r(A - C s)], E_R[r(C - A ns)]$
NS	$E_R[r(C - A ns)], E_R[r(A - C s)]$	$E[r(C)], E[r(C)]$

The strategies of the firm are described in the upper row, while the left column corresponds to those of the rival. Decision irreversibility and reversibility processes are explicitly differentiated through the payoffs defining the (S, NS) and (NS, S) entries of their respective matrices.

We analyze formally below the revenues that firms expect to obtain based on the different threshold values defining the optimal information gathering behavior of decision makers and the number of competitors existing in each particular market.

12.3 Absence of niche markets

Refer to Figures 18 and 19 and denote by $E[r(k)]$ the expected revenue obtained by each firm when both firms compete for decision makers within the $k = B, C$ optimal threshold framework. We describe below, both formally and intuitively, the elements composing these expected revenues for both firms.

Denote by $P(f)$ the [subjective] probability assigned by a firm to the decision maker observing a characteristic from one of its goods when competing [for decision makers] with a rival. Within a basic duopoly scenario, the probability assigned by a firm to the decision maker observing a characteristic from one of the goods offered by the rival equals $P(r) = 1 - P(f)$. Given the numerical simulations presented in the previous section, the probability that the decision maker continues gathering information on the good whose first characteristic she has observed can be easily defined and calculated. Denote this probability by $g(k) = (x_1^M - k)/(x_1^M - x_1^m)$, for $k = A, B, C$.⁶ Similarly,

⁶Abusing notation, we refer to k as both an information gathering threshold value and its projection on the X_1 domain.

the probability that the decision maker does not continue gathering information on the good whose first characteristic she has observed is given by $1 - g(k) = (k - x_1^m)/(x_1^M - x_1^m)$, for $k = A, B, C$.⁷

The firm's expected revenue when two pieces of information are left to gather and firms compete with each other for decision makers at k , where $k = B, C$, is given by⁸

$$E[r(k)] = P(f)[g(k)r_1(k) + (1 - g(k))[P(f)g(ce_1)r]] + \\ P(r)[(1 - g(k))[P(f)g(ce_1)r]],$$

where $r_1(k)$ represents the firm's expected revenue when one piece of information is left to gather and $x_1 > k$, with $k = A, B, C$. That is,

$$r_1(k) = h(P^+(x_1))r,$$

⁷We have assumed that both the firm and its rival have identical uniform distributions of available characteristics defined on the X_1 and X_2 sets. Thus, both firms face the same continuation and rejection probabilities in both the signaled and unsignaled markets. Note, however, that allowing for varying distributions of available characteristics between firms would modify their expected payoffs and the resulting equilibria.

⁸Note that the value of $g(ce_1)$ defined within the signaled market must be higher than the corresponding $g(ce_1)$ value defined within the unsignaled one. This is due to $E_{2|\theta=1} > E_2$ and the fact that decision makers consider the current set of unsignaled goods as the reference point upon which technological improvement must be defined. Imposing such a distinction explicitly would not affect the main results obtained but requires additional notation. Thus, while keeping the existing difference in mind, the notation will remain unchanged through the rest of the thesis.

where $h(P^+(x_1))$ denotes the probability assigned by the firm to the decision maker observing a x_2 value such that $u_2(x_2) > E_1 + E_2 - u_1(x_1)$ and r is the revenue obtained by the firm from the sale of its product.

When competing with a rival, firms face a probability $P(f)$ of having one of their goods' first characteristics observed by the decision maker. If this is the case, the probability of the decision maker observing a x_1 higher than the corresponding k value equals $g(k)$. After observing $x_1 > k$, the decision maker will observe a x_2 such that $u_1(x_1) + u_2(x_2) > E_1 + E_2$ with probability $h(P^+(x_1))$, and purchase the good, leading to a firm's revenue of r . However, if $u_1(x_1) + u_2(x_2) < E_1 + E_2$, the decision maker remains without any observation left to gather and, due to the terminal condition imposed, would not purchase any good, leading to a revenue of zero. On the other hand, if $x_1 < k$, an event taking place with probability $(1 - g(k))$, it has been assumed that the decision maker may observe a new first characteristic from the set of goods offered by any of the firms. In this case, if the decision maker observes her final first characteristic from one of the firm's goods, she will only purchase it if $x_1 > ce_1$, an event taking place with probability $g(ce_1)$, where $g(ce_1) = (x_1^M - ce_1)/(x_1^M - x_1^m)$.

The second term on the right hand side of the $E[r(k)]$ expression corresponds to the expected revenue of a firm when the decision maker gathers her first observation from one of the rival's goods. The firm will only be able to obtain a revenue if the decision maker observes a $x_1 < k$ characteristic from its rival's good and then chooses the firm to gather her final piece of

information, observing a value of $x_1 > ce_1$.

Note, finally, that the $E[r(k)]$ expression can be simplified and rewritten as follows

$$E[r(k)] = P(f)r[g(k)h(P^+(x_1)) + (1 - g(k))g(ce_1)], \quad k = B, C.$$

12.3.1 Guaranteed improvement

Within the guaranteed improvement framework, $E[r(B|s)]$ and $E[r(C|ns)]$ correspond to the expected revenue obtained by a firm from unilaterally signaling or not doing so, respectively. The expected payoff received by the signaling firm within an unilateral signaling scenario would be given by

$$E[r(B|s)] = r[g(B)h(P^+(x_1)) + (1 - g(B))g(ce_1)].$$

In this case, due to the guaranteed improvement assumption, decision makers will limit their search to the signaled market when gathering both of their available observations. Thus, if only one firm signals, it will serve alone all decision makers with respect to threshold B . The expected payoff obtained by the not signaling firm would therefore be given by

$$E[r(C|ns)] = 0.$$

Clearly, $E[r(B|s)] > E[r(B)]$ and $E[r(C|ns)] < E[r(C)]$. However, as we saw in the previous section, comparisons between $E[r(B)]$ and $E[r(C)]$ depend on the relative values of the cumulative probabilities $h(P^+(x_1))$ and $g(ce_1)$. As a result, we will not impose any constraint on the behavior of

$\frac{\partial E[r(k)]}{\partial k}$ or regarding the relative values of $E[r(B)]$ and $E[r(C)]$ when analyzing and defining the different sets of game equilibria.

As intuition would suggest, if both firms signal the improvement, they must compete for decision makers in the corresponding market, leading to a strictly smaller expected payoff, $E[r(B)]$, than the one obtained in a monopolistic environment by the firm that has signaled the improvement, $E[r(B|s)]$. In the latter case, the firm not signaling the improvement, and receiving $E[r(C|ns)]$, would be expected to suffer a loss relative to the not signaling equilibrium payoff, $E[r(C)]$, as decision makers shift their information gathering process to the signaled market.

However, and despite the induced decrease in competition, unilaterally signaling leads to a stricter threshold continuation criterion being imposed by decision makers on the corresponding set of goods. Thus, the incentives of firms to signal a technological improvement should depend on the relative magnitude of both these effects on their expected revenues.

12.3.2 Decision irreversibility

The set of expected revenues derived from the *decision irreversibility* setting is slightly more cumbersome than that of the guaranteed improvement case. We have denoted by $E_I[r(A - C|s)]$ the expected payoff received by the signaling firm when only one of them signals and decisions are irreversible, i.e. the decision maker foregoes the x_1 characteristic observed in the unsignaled market when moving to the signaled one. In this case, the payoff received

by the not signaling firm has been denoted by $E_I[r(C - A|ns)]$. Both these payoffs, and the corresponding ones that will be derived within the *decision reversibility* scenario, will be explicitly defined to capture *consumption inertia* in the information gathering process of decision makers. In our current setting, such an assumption implies that despite the technological superiority of the set of signaled goods, decision makers may be reluctant to initially shift their information gathering processes to the signaled market.⁹ As a result, decision makers could still gather their first observation from the unsignaled market and shifting may take place afterwards.

Consider the irreversible unilateral signaling scenario from the perspective of the not signaling firm and define its expected payoff by

$$E_I[r(C - A|ns)] = P(f)[g(A)r_1(A)] + P(r)[(1 - g(B))P(f)g(A)r]$$

If a decision maker gathers her first observation from the [set of goods offered by the] not signaling firm and it is lower than A , an event happening with probability $P(f)(1 - g(A))$, then she will shift to the signaled market in order to gather her last observation, leading to a payoff of zero for the not signaling firm. For consistency purposes, the second right hand side term

⁹That is, as emphasized by Malerba et al. (2003), the introduction of a new product within a given industry relies on the existence of experimental consumers that may allow for its survival through the creation of specialized niche markets. Similarly, the existence of network effects could also provide the intuition required to justify consumption inertia, as it is always challenging for decision makers to be among the first consumers of a new technology while abandoning an already established one.

of the equation requires the last x_1 gathered from the unsignaled market to be above A for the decision maker to choose the corresponding good and nothing otherwise.¹⁰

More precisely, the choice of threshold value within the final right hand side term allows for the following possibilities.

Assume that the decision maker observes a $x_{1|\theta=1} < B$ characteristic and shifts her information gathering process to the unsignaled market. In this case, observing a $x_1 > A$ characteristic leads to a higher expected utility than the one derived from the unsignaled certainty equivalent good. Besides, it also implies that the decision maker would rather continue gathering additional information on the observed unsignaled good than start gathering information on any of the [remaining] goods available in the signaled market. Therefore, A seems a reasonable candidate to consider as threshold value. Similarly, observing a characteristic located within (ce_1, A) implies that even though the expected utility derived from this observed good is above that of the certainty equivalent one defined *within the unsignaled market*, the decision maker would rather shift her information gathering process to the signaled market. In this case, the conflicting incentives faced by the decision maker could allow us to conclude that she does not purchase any good. On the other hand, we could also state that since information gathering decisions

¹⁰Note that, even if we take ce_1 as the reference point instead of A , we get $E_I[r(C - A|ns)] < E[r(B)]$, as is required in the following subsection to define the irreversible subgame equilibria.

are irreversible and the good observed in the unsignaled market satisfies the certainty equivalent requirements imposed by the decision maker, she purchases it. This would be the case despite the better expectations on the set of X_2 characteristics resulting from a random choice within the signaled market. As a result, ce_1 should act as the corresponding threshold value.

A similar analysis could be performed to describe $E_I[r(A - C|s)]$, where

$$E_I[r(A - C|s)] = P(f)[g(B)r_1(B) + (1 - g(B))P(f)g(ce_1)r] + P(r)[(1 - g(A))g(ce_1)r].$$

There exists a substantial difference between the assumptions underlying $E_I[r(A - C|s)]$ and those used to define $E[r(k)]$, with $k = B, C$. In both $E[r(k)]$ cases, if the decision maker observed a $x_1 < k$ characteristic from a firm's good, it was assumed that she could start gathering her second information piece from any of the two firms. In the current setting, decision makers are not indifferent between both markets if $x_1 < A$ in the unsignaled one. That is, once the initial inertia is overcome, decision makers will shift their information gathering process to the signaled market if $x_1 < A$ in the unsignaled one. However, if $x_1 < B$ in the signaled market, it has been assumed that decision makers may still gather their last piece of information from the signaled market with probability $P(f)$. These assumptions have been imposed to reflect the preference for experimentation that decision makers must exhibit after becoming aware of the existence of technologically superior products and despite the initial consumption inertia they may be subject to. Similar assumptions will hold in the *decision reversibility* setting.

However, the ability of decision makers to reverse their information gathering process back to the unsignaled market will introduce several modifications when defining the corresponding expected payoffs of firms.

12.3.3 Equilibria and results

Given the set of expected payoffs defined above, three possible technological transition matrices with their corresponding equilibria could be defined in period zero.

If $E[r(C)]$ is higher than $E[r(B|s)]$ and $E_I[r(A - C|s)]$, then a not signaling strategy from the firm in period zero implies that the rival will not signal in period one. Similarly, since $E[r(C|ns)] = 0$ and $E_I[r(C - A|ns)] < E[r(B)]$, we have

Technological Transition Matrix Period Zero

	S	NS
S	$E[r(B)], E[r(B)]$	
NS		$E[r(C)], E[r(C)]$

The subgame perfect equilibrium depends on the relative values of $E[r(B)]$ and $E[r(C)]$. In this case, both firms may coordinate their strategies in equilibrium by either signaling or not the existence of a technologically improved set of goods. However, it immediately follows that

Proposition 12.3.1 *If $E[r(B|s)] < E[r(C)]$ and $E_I[r(A - C|s)] < E[r(C)]$, the technological transition game has a unique subgame perfect equilibrium, (NS, NS) .*

Proof. If $E[r(B|s)] < E[r(C)]$ and $E_I[r(A - C|s)] < E[r(C)]$, then not signaling is a dominant strategy for both firms if $E[r(B)] < E[r(C)]$. This is indeed the case since $E[r(B|s)] > E[r(B)]$ and $E_I[r(A - C|s)] > E[r(B)]$. Thus, $E[r(C)] > E[r(B)]$, and not signaling constitutes the unique subgame perfect equilibrium. ■

In the guaranteed improvement case, if $E[r(B|s)] > E[r(C)]$, then a not signaling strategy from the firm in period zero implies that the rival will signal in period one, leading to

Technological Transition Matrix Period Zero

	S	NS
S	$E[r(B)], E[r(B)]$	$E[r(B s)], 0$
NS		

Clearly, the subgame perfect equilibrium consists of both the firm and its rival signaling the existence of an improved technology in period zero. Note that a relatively high $E[r(B|s)]$ payoff provides firms with a strong incentive to signal the existence of a technologically superior product. In this case, both firms will try to be the first one to signal, as if they were competing on a technological race where the winner enjoys the monopolistic rents reflected by the $E[r(B|s)] > E[r(C|ns)]$ inequality.

In the irreversible case, if $E_I[r(A - C|s)] > E[r(C)]$, then a not signaling strategy from the firm in period zero implies that the rival will signal in period one, leading to

Technological Transition Matrix Period Zero

	S	NS
S	$E[r(B)], E[r(B)]$	$E_I[r(A - C s)], E_I[r(C - A ns)]$
NS		

The subgame perfect equilibrium depends on the relative values of $E[r(B)]$ and $E_I[r(C - A|ns)]$. Given the assumptions imposed when defining $E_I[r(C - A|ns)]$ and the fact that $g(A) < g(B)$, it can be easily shown that $E_I[r(C - A|ns)] < E[r(B)]$, making of signaling an equilibrium strategy for the firm.¹¹ The following result is immediate.

Proposition 12.3.2 *If $E[r(B|s)] > E[r(C)]$ and $E_I[r(A - C|s)] > E[r(C)]$, the technological transition game has a unique subgame perfect equilibrium where both firms signal.*

Clearly, niche markets are *not* generated within any of these settings. In both cases, technological transition either takes place or does not, depending

¹¹Note that, if our assumptions are modified, in particular those regarding preference for experimentation, not signaling may become an optimal strategy, leading to the creation of niche markets signaled by the rival. We will however maintain the current behavioral assumptions to emphasize the fact that the same set of constraints may lead to the creation of technological niche markets when decision reversibility is allowed for.

on the relative values attained by $E[r(B|s)]$ and $E_I[r(A - C|s)]$. We will illustrate in the following section how the absence of niche markets within the previous settings is mainly due to the relative [expected] payoff loss suffered by the firms that do not signal when the rival does.

12.4 Generating niche markets

Decision reversibility allows firms to coordinate the creation of niche markets in the interim period after observing the signaling strategy of the rival, a task significantly harder to achieve in the previous decision settings.

The reversible case follows a similar logic to the irreversible one. However, as we will show below, $E_R[r(C - A|ns)] > E_I[r(C - A|ns)]$ and $E_R[r(A - C|s)] < E_I[r(A - C|s)]$, which would allow for the generation of technological niche markets if $E_R[r(C - A|ns)] > E[r(B)]$ and $E_R[r(A - C|s)] > E[r(C)]$. Note that, given the behavioral implications derived from [and the assumptions imposed on] the rational information gathering process of decision makers, this type of equilibrium does not arise in the previous scenarios, since $E[r(C|ns)] < E_I[r(C - A|ns)] < E[r(B)]$. Thus, the ability of decision makers to reverse their information gathering processes becomes a necessary condition for technological niche markets to emerge.

12.4.1 Decision reversibility

Consider the reversible unilateral signaling setting from the point of view of the not signaling firm and define its expected payoff by

$$E_R[r(C - A|ns)] = P(f)[g(A)r_1(A)] + P(r)[(1 - g(B))P(f)g(A)r] +$$

$$g(ce_1 - A)\gamma(x_{1|\theta=1} < x_{1|\theta=1}^*)r,$$

where $\gamma(x_{1|\theta=1} < x_{1|\theta=1}^*)$ denotes the probability of the decision maker observing a $x_{1|\theta=1}$ in the signaled market lower than $x_{1|\theta=1}^*$, which is the $x_{1|\theta=1}$ value required for her to be indifferent between the good in the signaled market and that observed in the unsignaled one, i.e. $u_1(x_{1|\theta=1}^*) = u_1(x_1) + E_2 - E_{2|\theta=1}$. Note that the set of goods defining this additional term are preferred to the certainty equivalent one since x_1 must be located within the (ce_1, A) interval for this case to be considered, where $g(ce_1 - A)$ is the probability of $x_1 \in (ce_1, A)$.

A similar analysis could be performed to describe $E_R[r(A - C|s)]$, where

$$E_R[r(A - C|s)] = P(f)[g(B)r_1(B) + (1 - g(B))P(f)g(ce_1)r] +$$

$$P(r)[(1 - g(A))g(ce_1)\gamma(x_{1|\theta=1} > x_{1|\theta=1}^*)r].$$

The only difference with the irreversible case is the addition of $\gamma(x_{1|\theta=1} > x_{1|\theta=1}^*)$ to the $P(r)$ expression on the right hand side of the equation. In this case, the signaling firm must not only provide an improvement over ce_1 when the decision maker shifts her information gathering process, but also over

whatever observation gathered in the unsignaled market and located within the (ce_1, A) interval that may lead to a higher expected utility than the $x_{1|\theta=1}$ observed in the signaled market. Note that, if $\gamma(x_{1|\theta=1} > x_{1|\theta=1}^*) = 1$, $\forall x_1 \in (ce_1, A)$, then $E_R[r(A - C|s)] = E_I[r(A - C|s)]$. However, if $\gamma(x_{1|\theta=1} > x_{1|\theta=1}^*) < 1$, then $E_R[r(A - C|s)] < E_I[r(A - C|s)]$.

12.4.2 Equilibria and results

The set of reversible equilibria depends on the relative strength of the reversibility effect, given by the value of the $\gamma(x_{1|\theta=1})$ function within the $E_R[r(C - A|ns)]$ and $E_R[r(A - C|s)]$ expressions. Reversibility constitutes a gain over $E_I[r(C - A|ns)]$ for the not signaling firm, while imposing a loss relative to $E_I[r(A - C|s)]$ on the signaling one if $\gamma(x_{1|\theta=1} > x_{1|\theta=1}^*) < 1$.

Given the set of expected payoffs defined in the previous section, four possible technological transition matrices, with their corresponding equilibria, could be defined in period zero.

If $E[r(C)]$ is higher than $E_R[r(A - C|s)]$, then a not signaling strategy from the firm in period zero implies that the rival will not signal in period one. At the same time, the reversibility effect prevents us from being able to guarantee that $E_R[r(C - A|ns)] < E[r(B)]$, which leads to either one of the following matrices

Technological Transition Matrix Period Zero (I)

	S	NS
S	$E[r(B)], E[r(B)]$	
NS		$E[r(C)], E[r(C)]$

Technological Transition Matrix Period Zero (II)

	S	NS
S		
NS	$E_R[r(C - A ns)], E_R[r(A - C s)]$	$E[r(C)], E[r(C)]$

The subgame perfect equilibrium in (I) depends on the relative values of $E[r(B)]$ and $E[r(C)]$. In this case, as in the guaranteed improvement and irreversible ones, both firms may coordinate their strategies in equilibrium by either signaling or not the existence of a technologically improved set of goods.¹² On the other hand, not signaling becomes the unique dominant strategy for both firms in (II). Thus, the absence of unilateral signaling incentives together with a sufficiently large reversibility effect within $E_R[r(C - A|ns)]$ would prevent technological transition from taking place.

¹²Note that, in the decision irreversibility setting, the unique equilibrium of the game was given by a common not signaling strategy, since $E[r(C)] > E_I[r(A - C|s)] > E[r(B)]$. However, within the current reversibility scenario we have $E[r(C)] > E_R[r(A - C|s)] < E_I[r(A - C|s)]$, which prevents us from guaranteeing that $E[r(C)] > E[r(B)]$ and defining a unique not signaling equilibrium.

However, if $E_R[r(A - C|s)] > E[r(C)]$, then a not signaling strategy from the firm in period zero implies that the rival will signal in period one, leading to either one of the following matrices

Technological Transition Matrix Period Zero (i)

	S	NS
S	$E[r(B)], E[r(B)]$	$E_R[r(A - C s)], E_R[r(C - A ns)]$
NS		

Technological Transition Matrix Period Zero (ii)

	S	NS
S		$E_R[r(A - C s)], E_R[r(C - A ns)]$
NS	$E_R[r(C - A ns)], E_R[r(A - C s)]$	

The subgame perfect equilibrium in (i) depends on the relative values of $E[r(B)]$ and $E_R[r(C - A|ns)]$. Once again, and contrary to the other scenarios, we cannot guarantee that $E_R[r(C - A|ns)] < E[r(B)]$ [note that the reversibility effect prevents us also from guaranteeing that $E_R[r(C - A|ns)] < E_R[r(A - C|s)]$]. As a result, signaling does not necessarily become a dominant equilibrium strategy for both firms. This would only be the case if $E_R[r(C - A|ns)] < E[r(B)]$. However, if $E_R[r(C - A|ns)] > E[r(B)]$, the resulting market [niche] equilibria are illustrated in (ii).

The subgame perfect equilibria described in (ii) can be analyzed as two separate subcases defined by the relative values of $E_R[r(C - A|ns)]$ and

$E_R[r(A - C|s)]$. Technological niche markets emerge naturally in both cases but the incentives to participate as the signaling firm vary between them. Clearly, if $E_R[r(C - A|ns)] < E_R[r(A - C|s)]$, both firms will try to signal in the first place and become technological monopolists within the niche market, as is the case in standard technological race models. The generation of first mover advantages requires a relatively low payoff loss imposed by $\gamma(x_{1|\theta=1} > x_{1|\theta=1}^*)$ on the signaling firm as well as a relatively low gain from reversibility, via $\gamma(x_{1|\theta=1} < x_{1|\theta=1}^*)$, for the not signaling one. Therefore, low reversibility effects coupled with the existence of monopolistic rents, derived from $E_R[r(A - C|s)] > E[r(C)]$ and $E_R[r(A - C|s)] > E[r(B)]$, provide firms with the incentives required to signal and become sole technological monopolists, *even if these firms are already incumbents in a given niche market*.¹³ An example of this type of behavior is given by Apple's leapfrogging strategy in the introduction of the iPod Nano, even before newcomers could pose a serious threat within the market developed by the iPod Mini, creating and monopolizing its own technological niche market, see Li and Jin (2009).

¹³Note that nothing prevents a firm from sending two or more consecutive signals if further technological improvements are available; refer to Figures 18 and 19 for a numerical illustration of the two signals' case. In this case, an incumbent firm may consider sending a second signal if it expects a rival to signal and access its current niche market, which would lead to a relative payoff of $E[r(B)]$ for both firms. As a result, given the expected payoff received if both firms compete within the current niche market, the incumbent may have an incentive to signal again and distance itself from the current niche market by climbing a second quality ladder.

However, if $E_R[r(C-A|ns)] > E_R[r(A-C|s)]$, and even though both firms are better off within a technological niche market, the signaling firm would be suffering an expected payoff loss with respect to its [not signaling] rival. That is, the reversibility risk involved in signaling decreases the expected payoff derived from such a strategy while increasing that of the not signaling rival.¹⁴ This type of “second mover advantage” requires a relatively large gain from reversibility via $\gamma(x_{1|\theta=1} < x_{1|\theta=1}^*)$ for the not signaling firm as well as a relatively large payoff loss imposed by $\gamma(x_{1|\theta=1} > x_{1|\theta=1}^*)$ on the signaling one. In this sense, those firms whose set of available goods provides them with a large reversibility advantage [due, among others, to lock-in, bandwagon, network and reputation effects]¹⁵ have an incentive to let their rivals signal and monopolize a new technological niche market.

12.5 Quality ladders and the Arrow effect

The history friendly analysis of the evolution of the computer industry presented by Malerba et al. (1999, 2001) displays the latter type of equilibrium pattern. These authors show how the advances in component technologies driving the evolution of the computer industry were developed by newcomer

¹⁴Note that, if decisions are irreversible $E_I[r(C-A|ns)] < E_I[r(A-C|s)]$, $\forall x_1 \in X_1$.

¹⁵Regarding reputation and consumer education and their importance for the acquisition of newly developed products see Eng and Quaia (2009). Bandwagon and network effects are formally discussed and incorporated by Malerba et al. (2003) in their behavioral evolutionary model.

firms that managed to survive by supplying experimental consumers in technological niche markets. This innovation process was never undertaken by the incumbent firms dominating the existing component technology. In this regard, Malerba et al. (2003, 2007) emphasize the substantial uncertainty faced by incumbents when identifying the set of possible competing players. Indeed, these authors highlight the fact that the descriptive literature has shown how incumbents are subject to cognitive biases and organizational factors that play a major role in accounting for the fatal lag in their response when the new technology succeeds in getting a foothold, a phenomenon whose explanation is set aside by rational choice models; see Malerba et al. (2003: 6). As a result, they distance themselves from standard game theoretical settings when analyzing this type of phenomenon in favor of a behavioral evolutionary approach.

Our latter subcase illustrates how the “stylized facts” described by Malerba et al. (1999, 2001, 2003, 2007) may be derived as a subgame perfect equilibrium between competing duopolists when decision makers behave as perfectly rational utility maximizers. Note that this type of behavior differs substantially from the one dictated by the Arrow effect, considered by Grossman and Helpman (1991) and the subsequent literature on quality ladders to be the mechanism triggering the introduction of technologically superior products. In their setting, incumbents expect lower profits relative to newcomers from developing the next innovation. This difference incentivates newcomers to develop the next innovation and collect the benefits derived from the

corresponding technological monopoly. In our latter setting, incumbents and newcomers, both of which have already developed the next innovation, expect the next innovation to constitute a drawback for the signaling firm, which explains their reticence to signal its existence and create a niche market. This is indeed the case despite the fact that, given the available supply of products, creating a technological niche market is a [subgame perfect] Nash equilibrium based on the rational information gathering process and choice behavior of decision makers.

The emergence and prevalence of technological niche markets within the reversible game theoretical environment can be intuitively justified in several ways.

First, the assumption of symmetry defining both duopolists and leading to identical reversibility effects could be relaxed and a combination of the previous reversible subgame scenarios considered. In other words, inexperienced newcomers may be subject to the payoff constraints defined in (ii) [with $E_R[r(A - C|s)] < E_R[r(C - A|ns)]$] when deciding whether or not to signal while a reputed incumbent may play under those defined in (i) [with $E_R[r(C - A|ns)] < E[r(B)]$]. That is, if the newcomer decides to signal first, the existence of large reversibility effects would benefit the not signaling incumbent. However, a sufficiently low reversibility effect generated by the incumbent's signal would force the newcomer to wait and coordinate its signaling strategy at B .¹⁶

¹⁶Similarly, the strength of the signal, which determines the location of points A and

Second, an incorrect estimation of the gains derived from reversibility [loses imposed on the signaling firm] by the incumbent firm, i.e. miscalculating the payoffs and, therefore, the stability of the technological niche market, could lead to the creation of stable technological niche markets by a newcomer. It should be emphasized that accounting for network and bandwagon effects, as well as for future possible signals, requires defining several additional subjective probability functions, which may greatly differ between firms and significantly modify the entrances [subjective expected payoffs] of the corresponding transition matrices.

Finally, the existence of vintage effects, see Bohlmann et al. (2002), implies that later entrants utilizing improved technology can face lower costs and reach higher quality levels than the pioneer signaling firm. These authors show that pioneers in categories with high vintage effects tend to have lower market shares and higher failure rates. Moreover, they find key relationships between the magnitude of the pioneer advantage [or disadvantage] and the consumer valuation of product attributes such as variety and quality. In particular, their empirical results illustrate how pioneers do better in product categories where variety is more important and worse in categories where product quality is more important. That is, when variety becomes an B , could be assumed to be a function of the firm signaling. These scenarios could be further developed to explain, for example, why Microsoft waited for Sony to introduce its Playstation 2 before launching the Xbox, instead of competing directly within the existing Playstation market, see Li and Jin (2009) for an alternative theoretical proposal.

important characteristic the reversibility effects should decrease, promoting unilateral signaling strategies and the emergence of niche markets. However, quality considerations relate intuitively to [consumer] inertia-based frictions and should increase the relative importance of the reversibility effects, which would justify the reticence of firms to signal and create technological niche markets, despite the assumed credibility of the signals.

Chapter 13

Conclusion and extensions: the way from here

The importance of demand based industrial dynamics is a phenomenon becoming increasingly evident, see Klepper and Malerba (2010). Demand may influence technological evolution via the direct induction of innovations or indirectly through their diffusion processes. The current thesis has presented a decision theoretical model of [rational expected utility-based] demand for technologically superior products that provides a compatible perspective with the results obtained by the behavioral evolutionary economic literature.

We have illustrated how, after the observation of positive credible signals, decision makers become more prone to start a new search for a good better than the one whose first characteristic has been observed within the

corresponding signaled market. One of the main conclusions to be derived from this thesis is that positive signals do not only affect the calculation of certainty equivalent values but also the willingness to search of rational decision makers. That is, as the number of positive signals received increases, decision makers become more prone to start a new search for a good better than the one whose first characteristic has already been observed. At the same time, absent market frictions and myopia, the increase in expected values generated by positive signals triggers immediate herds among decision makers, who would only consider searching the goods belonging to the set on which the biggest number of signals is received.

Market frictions, coupled with full rationality, have been shown to be able to cause a slow-down in the adoption of both the currently available technology *and* the newly introduced superior one. In particular, we have shown how the presence of consumption inertia and search frictions may prevent immediate herds to the signaled market while inducing decision makers to require a much higher X_1 realization from the unsignaled one in order to remain gathering information on the sets of goods offered by the firms operating within it.

We have also analyzed the [strategic] consequences derived from the existence of path dependence phenomena by explicitly accounting for the process of information diffusion among decision makers and the emergence of bandwagon and network effects that may take place after firms signal the availability of a technologically superior set of goods.

It should be noted that the information acquisition incentives of decision makers have been defined through their expected search utilities, which, at the same time, define implicitly the revenues expected to be obtained by firms. That is, given the available distribution of product characteristics that may be displayed by a firm, its expected revenues depend on its ability to provide the characteristics required by decision makers. In this sense, we have assumed that market signals correspond to truthful fully credible reports. However, an immediate extension of the thesis should account for different possible types of strategic market interactions, since decision makers do not generally observe the real distributions of characteristics. That is, a principal may always issue signals so as to manipulate the choice of uninformed but perfectly rational agents. It should be emphasized that preference manipulation may occur even if the information transmitted is fully verifiable by the decision maker, see Di Caprio and Santos Arteaga (2011). Indeed, a single signal suffices to generate the herding mechanism described by Banerjee among decision makers. Thus, the strategic nature of the information transmission process should be explicitly analyzed in fields that do not currently account for it, such as knowledge management (Holsapple, 2003). This is particularly important at the organizational level, where relatively small sets of decision variables are generally considered (Gaines, 2003).¹ Similar remarks apply to the design of decision support systems and

¹In this regard, the model could be used to extend in an heterogeneous direction papers such as that of Li and Zhu (2009), where a group of homogeneous experts must be hired,

information dashboards that guide the process of managerial decision making (Adam and Pomerol, 2008).

In addition, the results obtained allow for a formal treatment of the optimal acquisition of information and choice processes considered by the consumer choice literature, where the strategic side of information transmission is rarely formalized (Ariely, 2000; Bearden and Connolly, 2007; Diehl, 2005; Novemsky et al., 2007).

From a supply perspective, we have identified the requirements necessary for the emergence of niche markets where firms signaling the availability of technologically superior goods may survive. We have designed a general equilibrium environment where rational consumers compose a demand driven system determining the selection of technologies when firms decide strategically whether or not to signal the existence of an already developed technologically superior set of goods. The concept of [endogenously defined] performance thresholds of Adner and Levinthal (2001) has arisen quite naturally within our environment and allowed us to analyze how consumer preferences influence the introduction of existing disruptive technologies, see Adner (2002). We have illustrated how, after the observation of positive credible signals, [perfect foresight] decision makers become more prone to start a new search for a good better than the one whose first characteristic has already been observed in the corresponding signaled market. Besides, as was also

either simultaneously or sequentially, to forecast the stochastic market demand for a new product that is about to be introduced.

the case in Ireland and Stoneman (1986), perfect foresight has been shown to cause a slow-down in adoption of the currently available technology relative to myopia. That is, even in the presence of consumption inertia and irreversible decisions, we have seen how perfect foresight decision makers require a much higher X_1 realization from the unsignaled market than myopic ones to remain gathering information on the sets of goods offered by the corresponding firm.

The micro-oriented approach to technological demand provided by the thesis complements macro-oriented evolutionary approaches such as that of Dolfsma and Leydesdorff (2009) when analyzing how technological processes may break-out of a trajectory. In particular, these authors include political decision-making processes as co-evolvers along trajectories together with markets and technologies. Following this type of reasoning within the current setting should help shedding some light on policy considerations, ranging from the public acquisition of technology to consumer education programs. That is, it seems natural to assume that less risk averse decision makers are more experienced and educated [in technological terms] than more risk averse ones, which makes them more experimental and less search averse than the less educated ones. Similarly, the ability of decision makers to observe and interpret signals may be assumed to depend on their experience and [technological] education. As a result, the existence of myopic [less educated] risk averse decision makers increases the probability of suboptimal

locking-in phenomena.² In this sense, myopic decision makers could be used to study the prevalence of local monopolies supplying technologically inferior products within developing countries and the failure of the latter ones to generate enough demand pull to foster further technological introductions.

The main results obtained through the game theoretical setting defining the supply side of the technological market when allowing for decision reversibility in the information gathering process of decision makers can be summarized as follows.

Consider an environment where decision makers are allowed to compare the characteristics of the goods observed in both markets, the signaled and the unsignaled one, before making a purchase. This setting leads to two main types of possible subgame perfect equilibria for the firms when deciding whether or not to introduce technologically superior products in the market.

First, a technological race where firms try to become the main monopolistic force within the corresponding niche market and a loss is inflicted on those firms that are unable to cope with the innovation, a result compatible with the findings of Buenstorf and Klepper (2010). In this case, the devel-

²Harty (2010) illustrates through several case studies how demand heterogeneity does not only affect the implementation and use given to a technology but also the expectations and requests placed on its future developments. An economic perspective is provided by van den Ende and Dolfsma (2005), who demonstrate how “the emergence of new technological paradigms can also be enabled by demand factors, whereas developments in technological knowledge may also exert influence within the boundaries of a paradigm” (pg. 85).

opment of technological niche markets reinforces the dominant position of the innovator, as is the case in the standard industrial organization literature. Thus, firms will signal the existence of a set of technologically superior products as soon as they are developed.

On the other hand, we have obtained equilibria where the generation of niche markets is suboptimal for the signaling firm, which should try to wait for the rival to signal the existence of the products first.³ In this case, the retreat strategy defined by Adner and Snow (2010), where the decision to stay with the old technology is a strategic choice made by the managers of a given firm, is formally obtained. However, and despite the rationality involved in the choice made by managers, Adner and Snow (2010) do not suggest that such a strategy is a dominant one to deal with technological change, while in our case it is.

Finally, note that the model introduced in this thesis has been designed with the highest possible degree of generality in mind. We are aware of the fact that important differences in consumer preferences, degrees of risk aversion, budget constraints and information gathering frictions arise depending on the markets and technological sectors under consideration. The current model should therefore be extended to account for these and other possible environmental effects affecting the information gathering and choice processes of decision makers.

³It should be noted that this type of “waiting races” have also been formally derived within the standard neoclassical literature, see Kapur (1995).

Appendix: numerical simulations

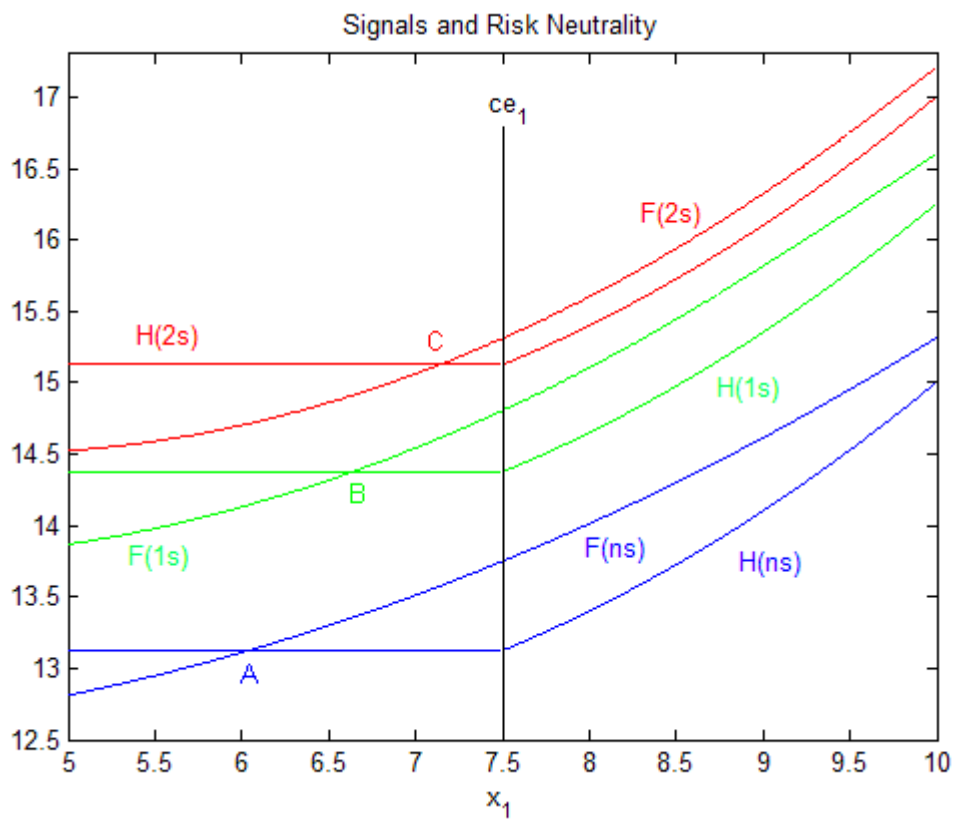
Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$

Error! Bookmark not defined. Utility functions: $u_1(x_1) = x_1$; $u_2(x_2) = x_2$

Probability densities: both continuous and uniform

$$\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}; \quad \forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$$

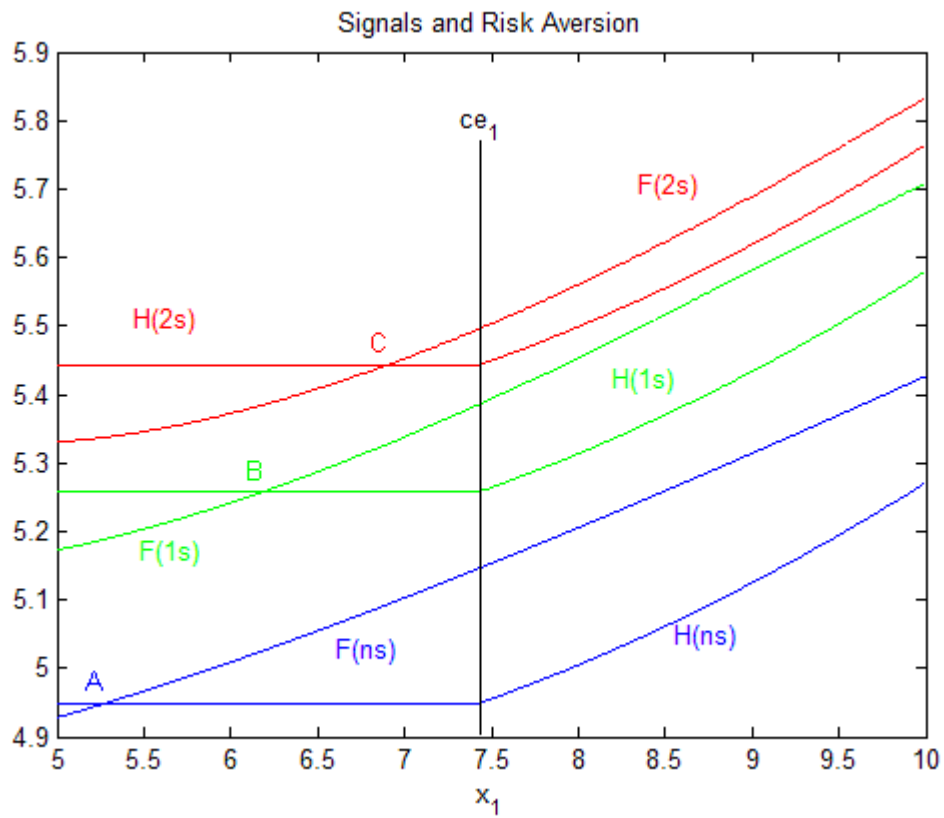
Figure 1



Evolution of optimal threshold values given risk neutral utility functions and uniform risk distributions.

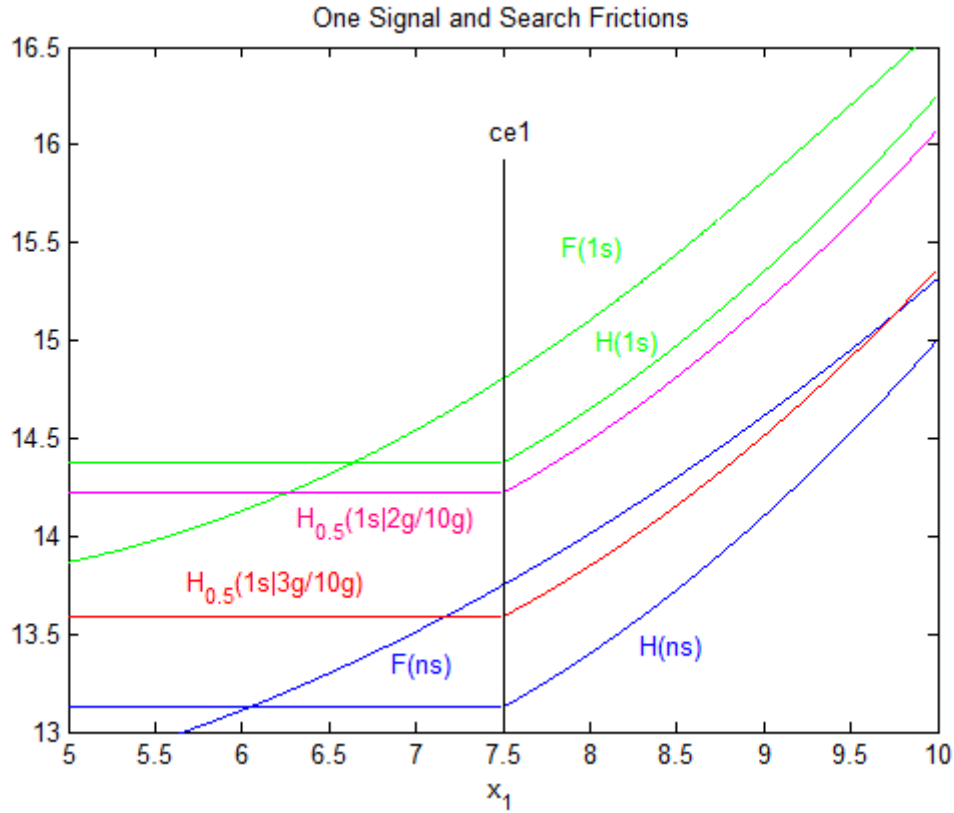
Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$
Error! Bookmark not defined.Utility functions: $u_1(x_1) = \sqrt{x_1}$; $u_2(x_2) = \sqrt{x_2}$
 Probability densities: both continuous and uniform
 $\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}$; $\forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$

Figure 2



Evolution of optimal threshold values given risk averse utility functions and uniform risk distributions.

Figure 3



Risk neutral environment as in Figure 1.

Same positive signal observed as the case in Figure 1.

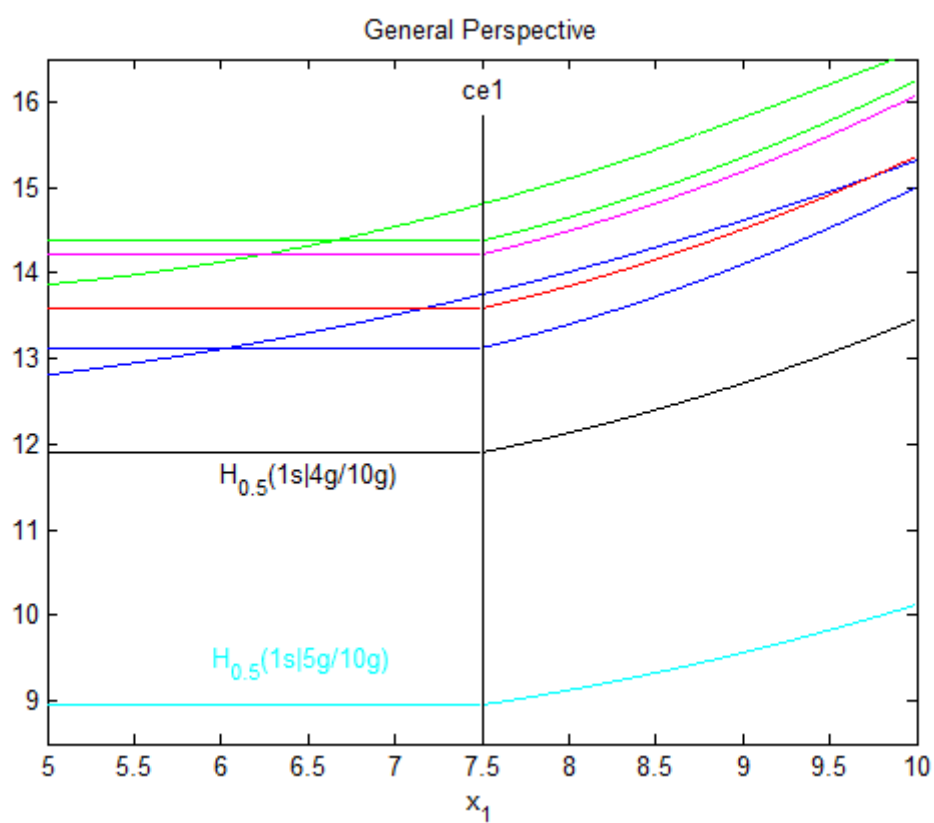
Example of search and matching frictions:

$H_{0.5}(1s|2g/10g)$ represents the original $H(1s)$ function weighted down by a binomial distribution $\psi(m, l, f)$ with the following coefficients: $m = 10$, $l = 2$, $f = 0.5$.

That is, we shift the f binomial coefficient from 1 to 0.5.

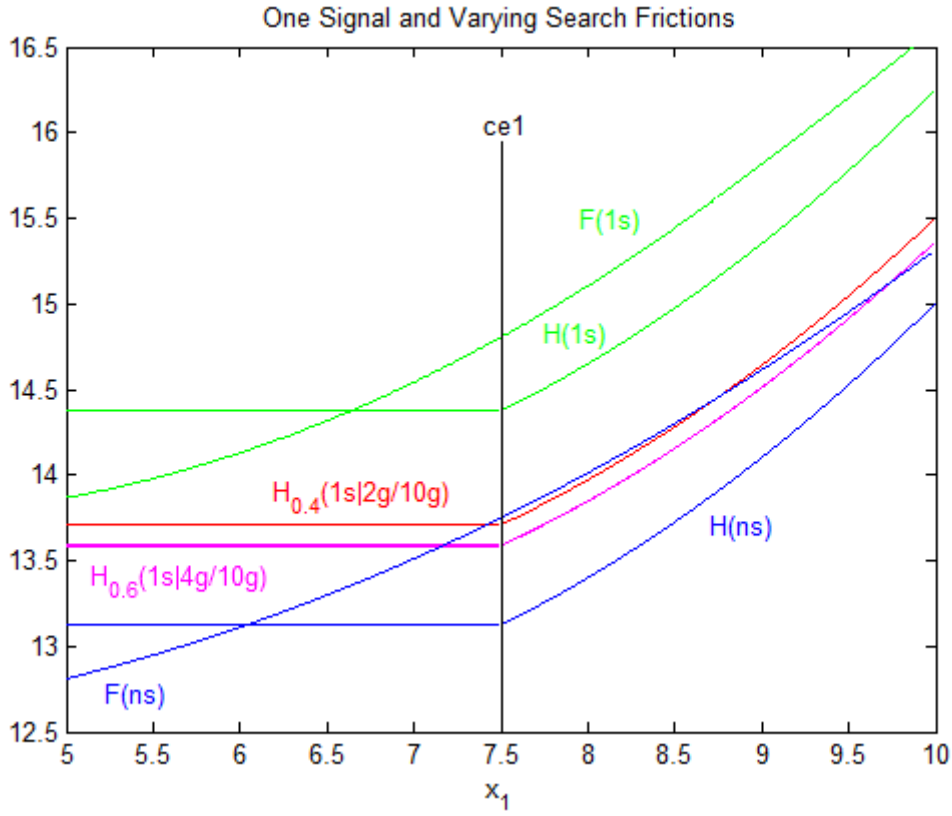
At the same time, the number of sufficiently diffused goods required by the decision maker to become available during the search process must be of at least two out of ten.

Figure 4



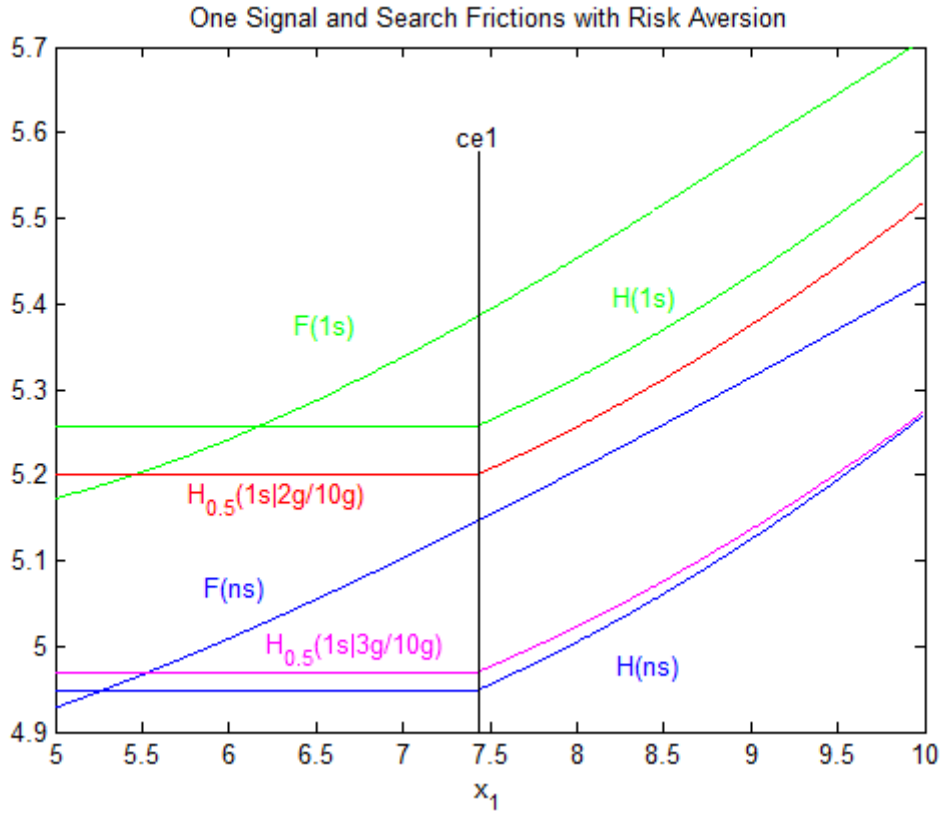
Risk neutral environment as in Figure 1
 Same positive signal observed as the case in Figure 1.
 Example of search and matching frictions: same as in Figure 3.

Figure 5



Risk neutral environment as in Figure 1
 Same positive signal observed as the case in Figure 1.
 Example of search and matching frictions: same interpretation as in Figure 3.
 In this case, $H_{0.6}(1s|4g/10g)$ overlaps with $H_{0.5}(1s|3g/10g)$.
 The latter has not been explicitly identified in the figure.

Figure 6



Risk averse environment as in Figure 2

Same positive signal observed as the case in Figure 2.

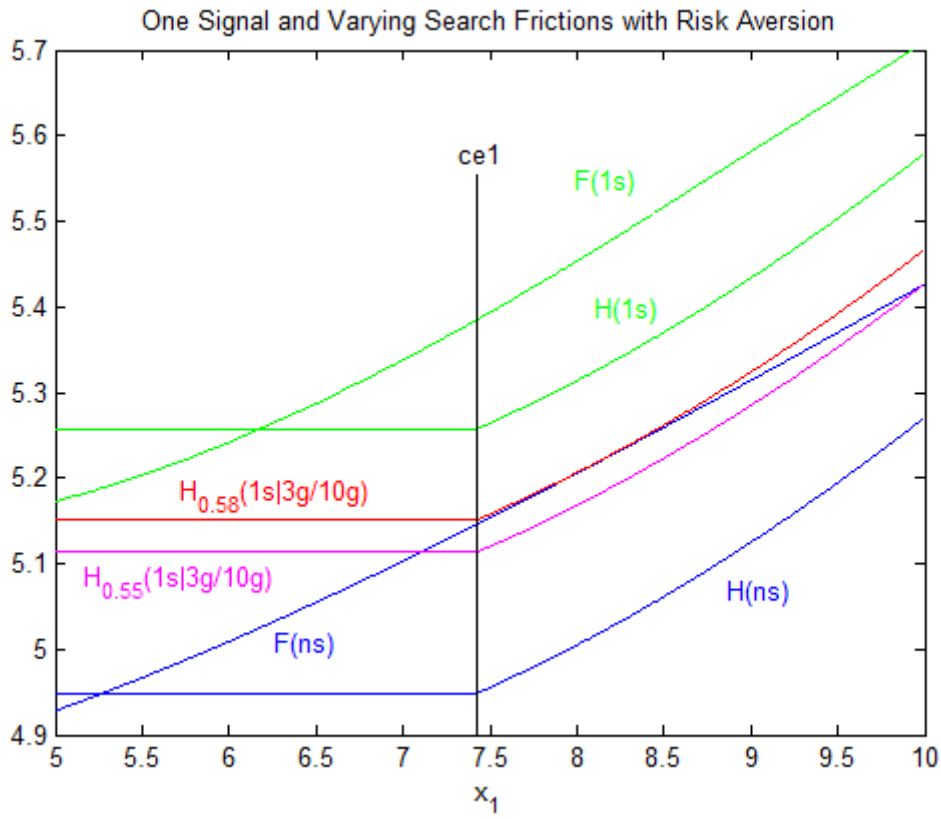
Example of search and matching frictions:

$H_{0.5}(1s|2g/10g)$ represents the original $H(1s)$ function weighted down by a binomial distribution $\psi(m, l, f)$ with the following coefficients: $m = 10$, $l = 2$, $f = 0.5$.

That is, we shift the f binomial coefficient from 1 to 0.5.

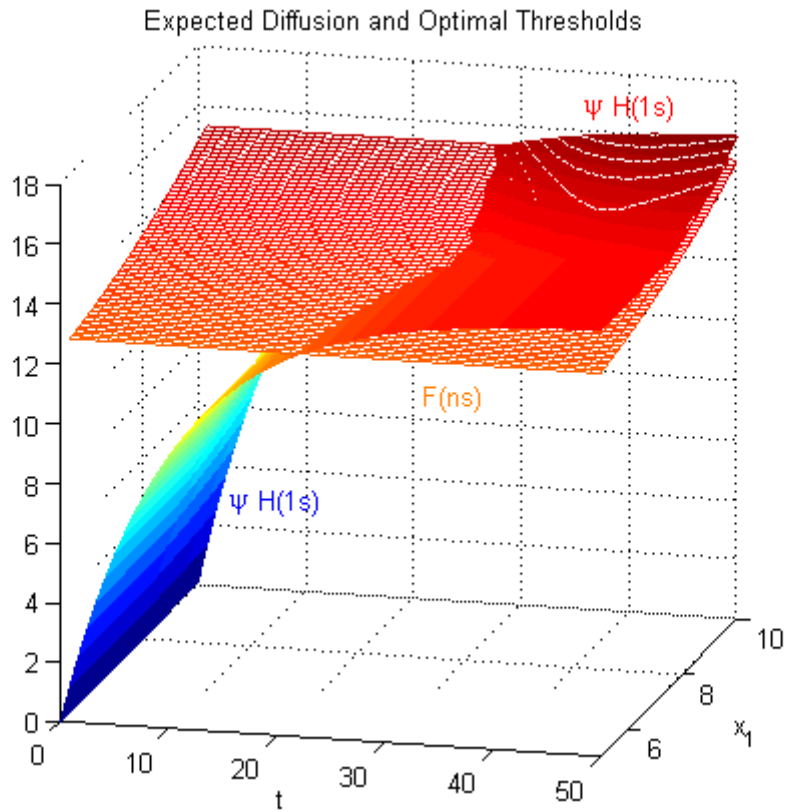
At the same time, the number of sufficiently diffused goods required by the decision maker to become available during the search process must be of at least two out of ten.

Figure 7



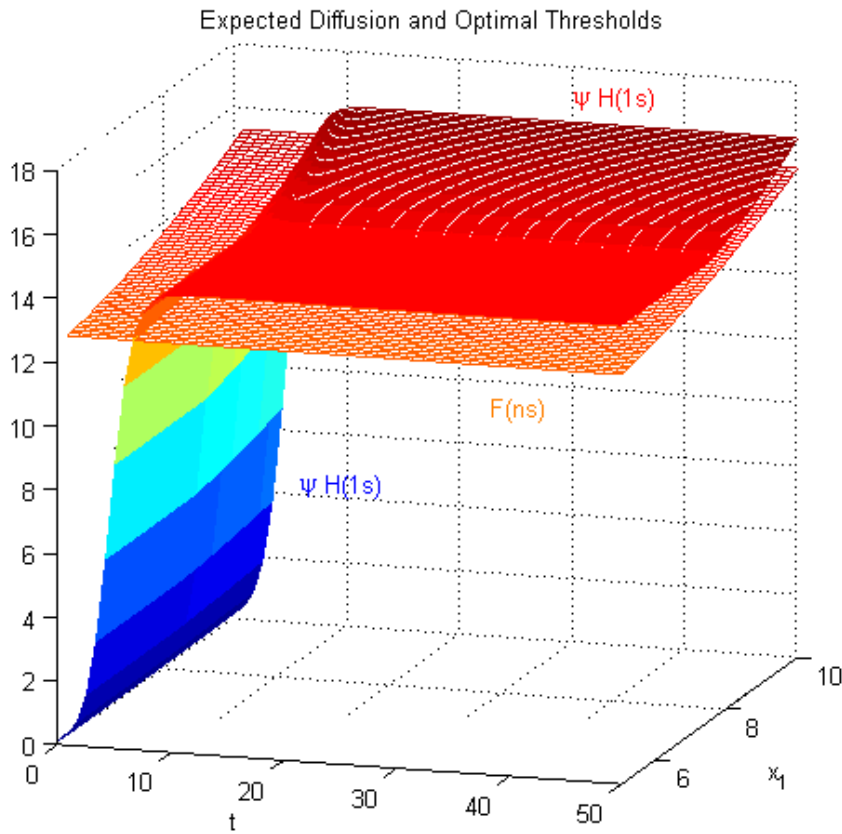
Risk averse environment as in Figure 2
 Same positive signal observed as the case in Figure 2.
 Example of search and matching frictions: same interpretation as in Figure 6.

Figure 8



Risk neutral environment as in Figure 1
 Same positive signal observed as the case in Figure 1.
 Basic diffusion with a centralized source.
 Example of network and diffusion effects:
 $\Psi H(1s)$ represents the original $H(1s)$ function weighted by a $\Psi_a(t)$ diffusion process
 with a coefficient $\alpha = 0.1$ and a duration of 50 time periods.

Figure 9



Risk neutral environment as in Figure 1

Same positive signal observed as the case in Figure 1.

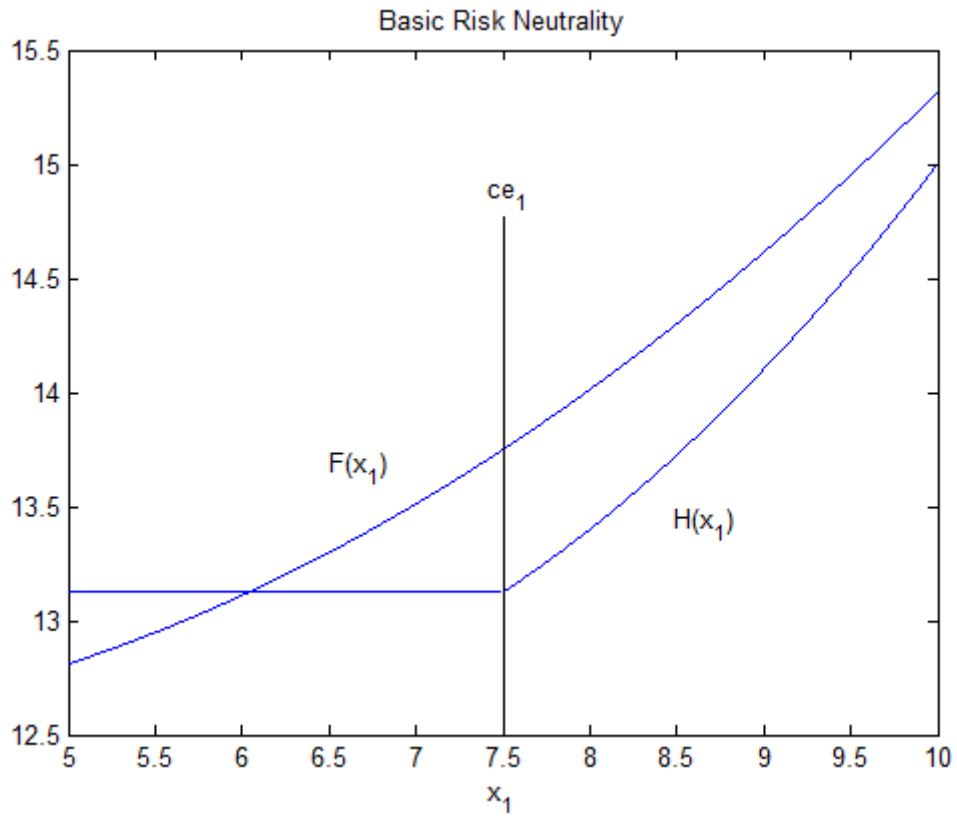
Basic diffusion with [word of mouth non-centralized] multiple sources.

Example of network and diffusion effects:

$\Psi H(1s)$ represents the original $H(1s)$ function weighted by a $\Psi_a(t)$ diffusion process with coefficients $\beta = 0.1$, $N = 10$, $\Psi_a(0) = 0.01$ and a duration of 50 time periods.

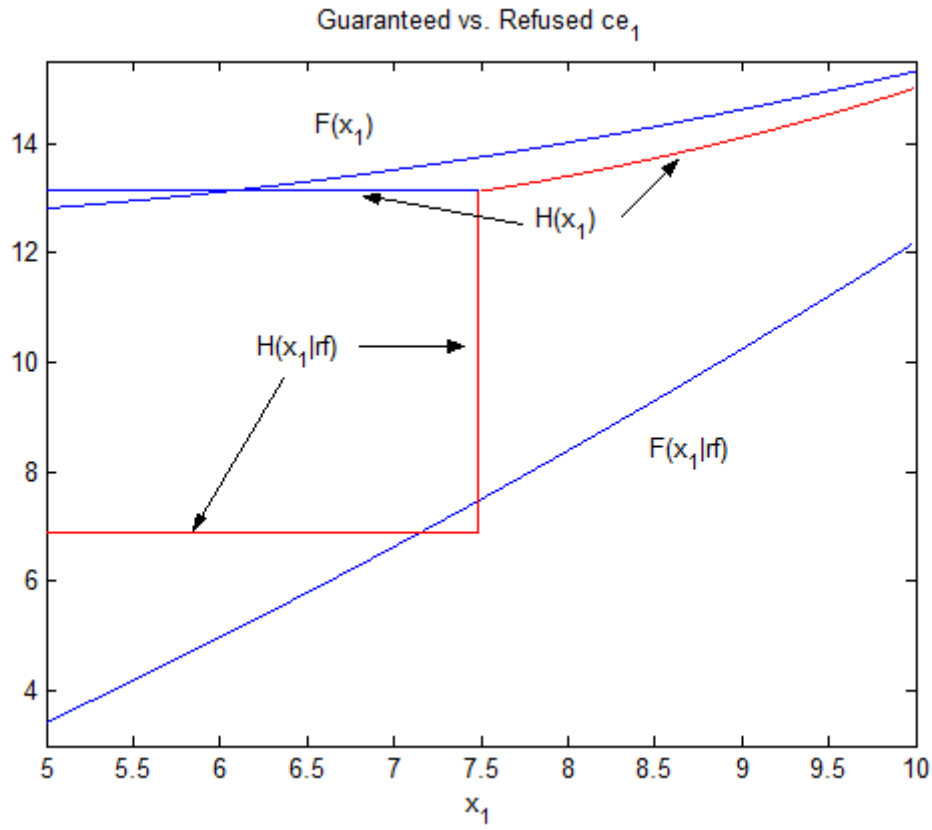
Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$
Error! Bookmark not defined.Utility functions: $u_1(x_1) = x_1$; $u_2(x_2) = x_2$
 Probability densities: both continuous and uniform
 $\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}$; $\forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$

Figure 10



Optimal threshold value given risk neutral utility functions and uniform risk distributions

Figure 11

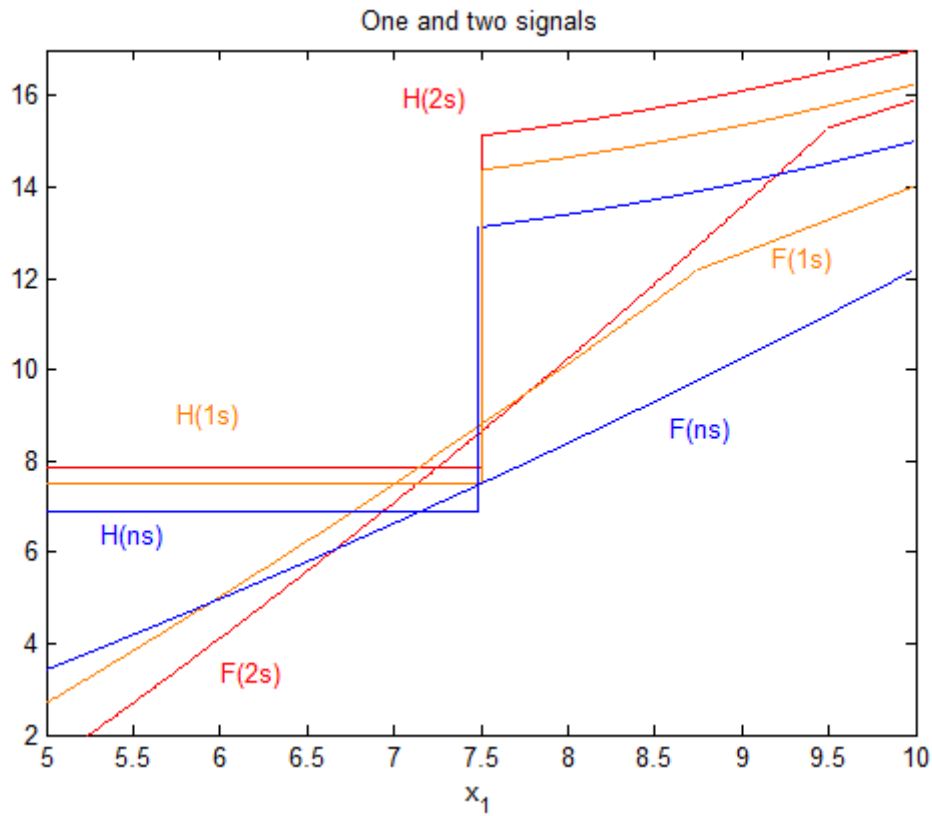


Guaranteed versus refused certainty equivalent scenarios:
threshold values and information gathering intervals

given risk neutral utility functions and uniform risk distributions.

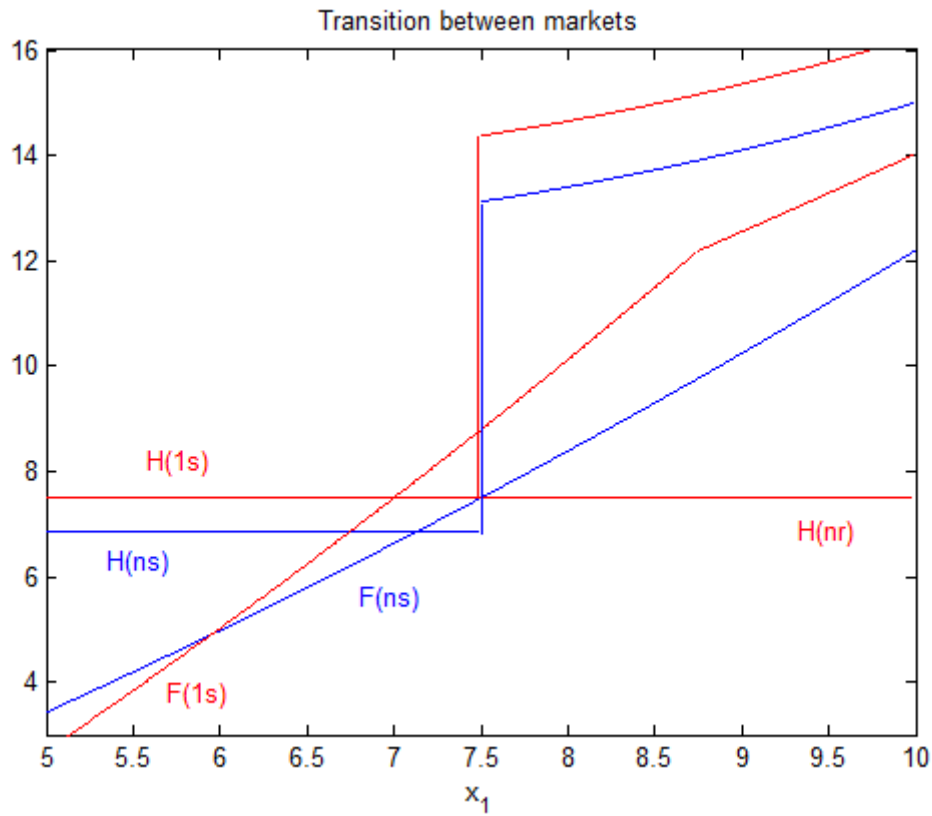
Note that the $H(x_1|rf)$ function is discontinuous. The vertical line joining both sections has been included to simplify the comparisons made between the g.c.e.s. and the r.c.e.s.

Figure 12



Refused certainty equivalent and multiple signals:
 threshold values and information gathering intervals
 given risk neutral utility functions and uniform risk distributions.
 Note that the $H(\cdot)$ functions are all discontinuous. The vertical lines joining their respective sections
 have been included to simplify the comparisons made between the g.c.e.s. and the r.c.e.s.

Figure 13



Refused certainty equivalent, signals and decision irreversibility:
threshold values and information gathering intervals
given risk neutral utility functions and uniform risk distributions.

Note that the $H(\cdot)$ functions are both discontinuous. The vertical lines joining their respective sections have been included to simplify the comparisons made between the g.c.e.s. and the r.c.e.s.

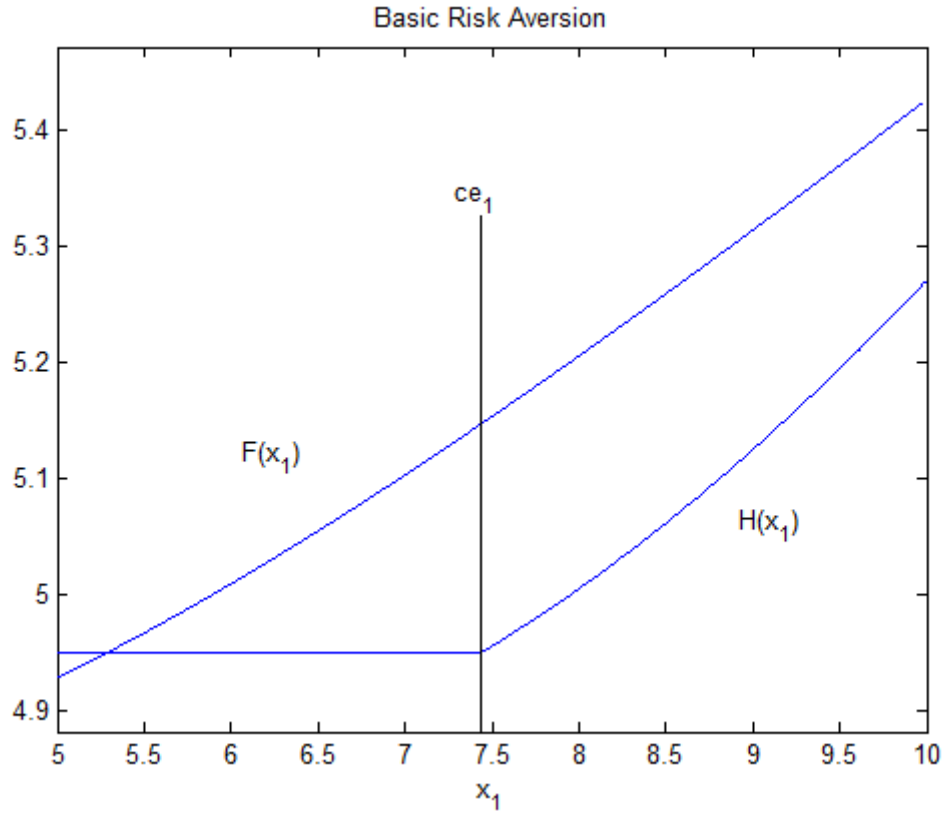
Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$

Error! Bookmark not defined.Utility functions: $u_1(x_1) = \sqrt{x_1}$; $u_2(x_2) = \sqrt{x_2}$

Probability densities: both continuous and uniform

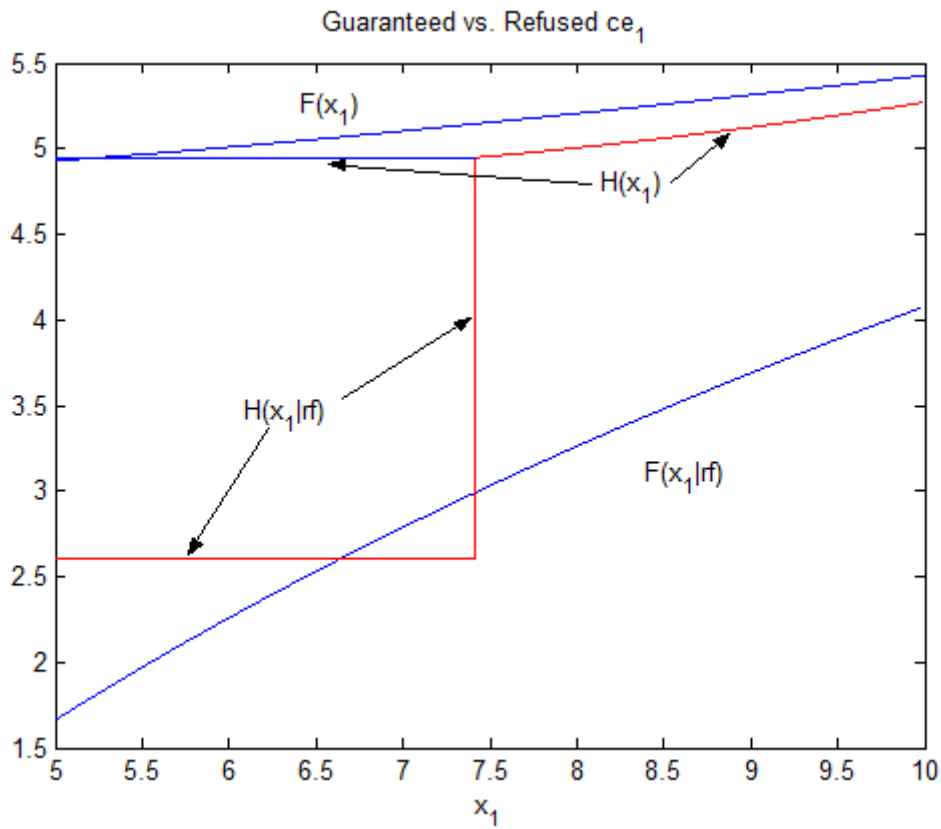
$$\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}; \quad \forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$$

Figure 14



Optimal threshold value given risk averse utility functions and uniform risk distributions

Figure 15

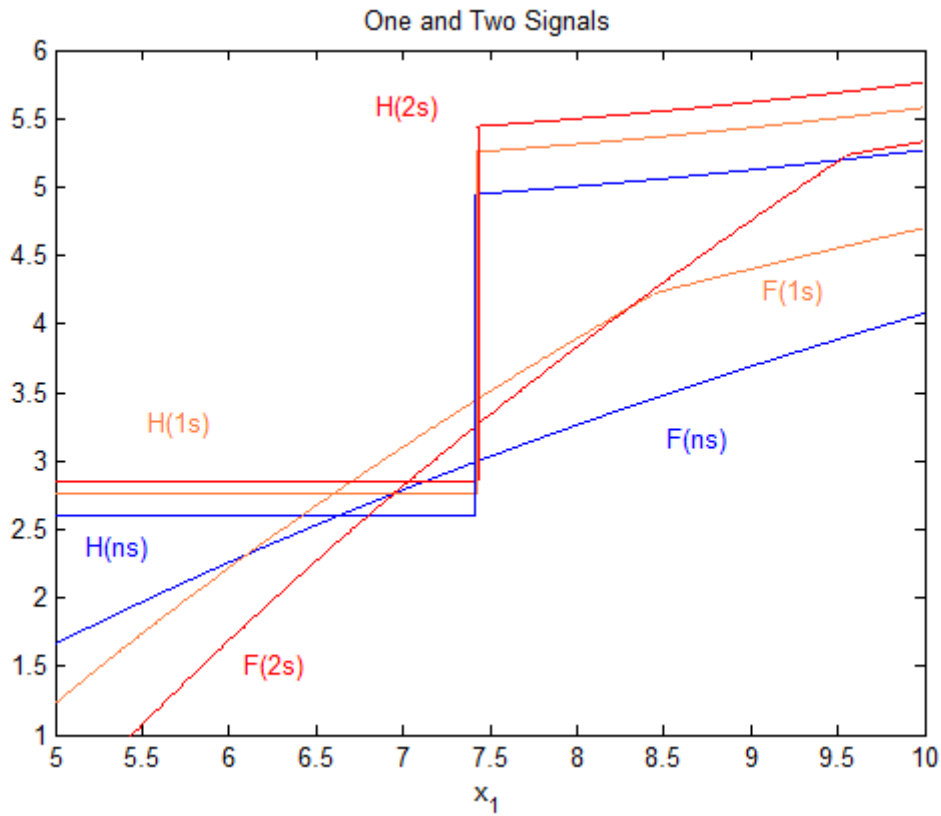


Guaranteed versus refused certainty equivalent scenarios:
threshold values and information gathering intervals

given risk averse utility functions and uniform risk distributions.

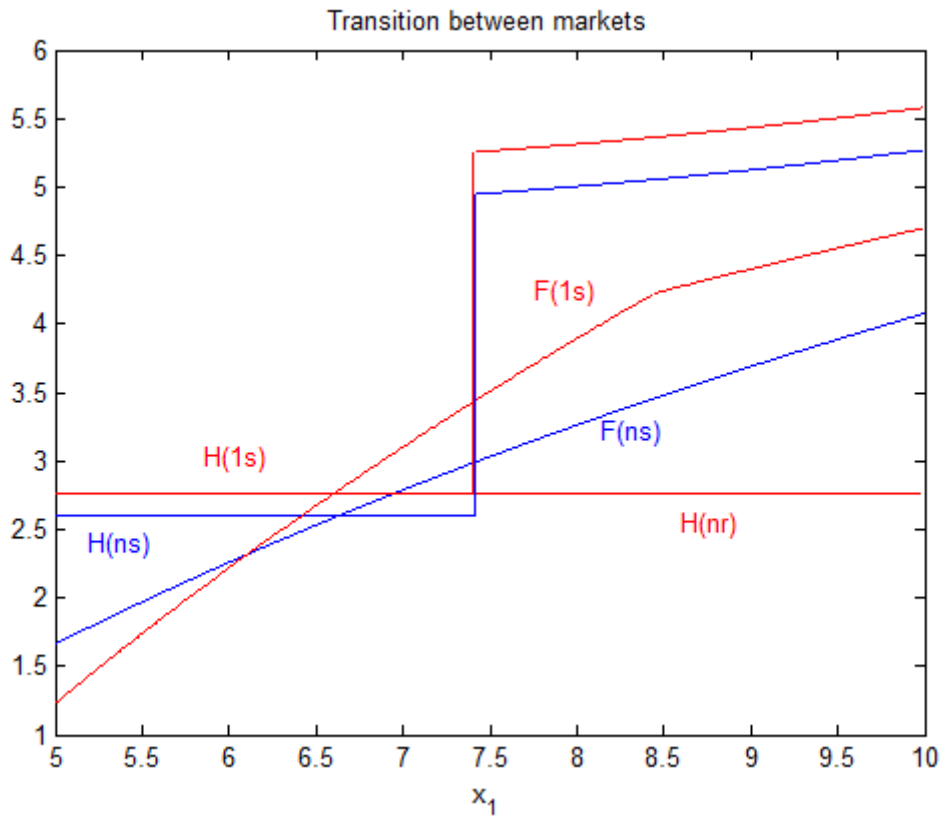
Note that the $H(x_1|rf)$ function is discontinuous. The vertical line joining both sections has been included to simplify the comparisons made between the g.c.e.s. and the r.c.e.s.

Figure 16



Refused certainty equivalent and multiple signals:
 threshold values and information gathering intervals
 given risk averse utility functions and uniform risk distributions.
 Note that the $H(\cdot)$ functions are all discontinuous. The vertical lines joining their respective sections
 have been included to simplify the comparisons made between the g.c.e.s. and the r.c.e.s.

Figure 17

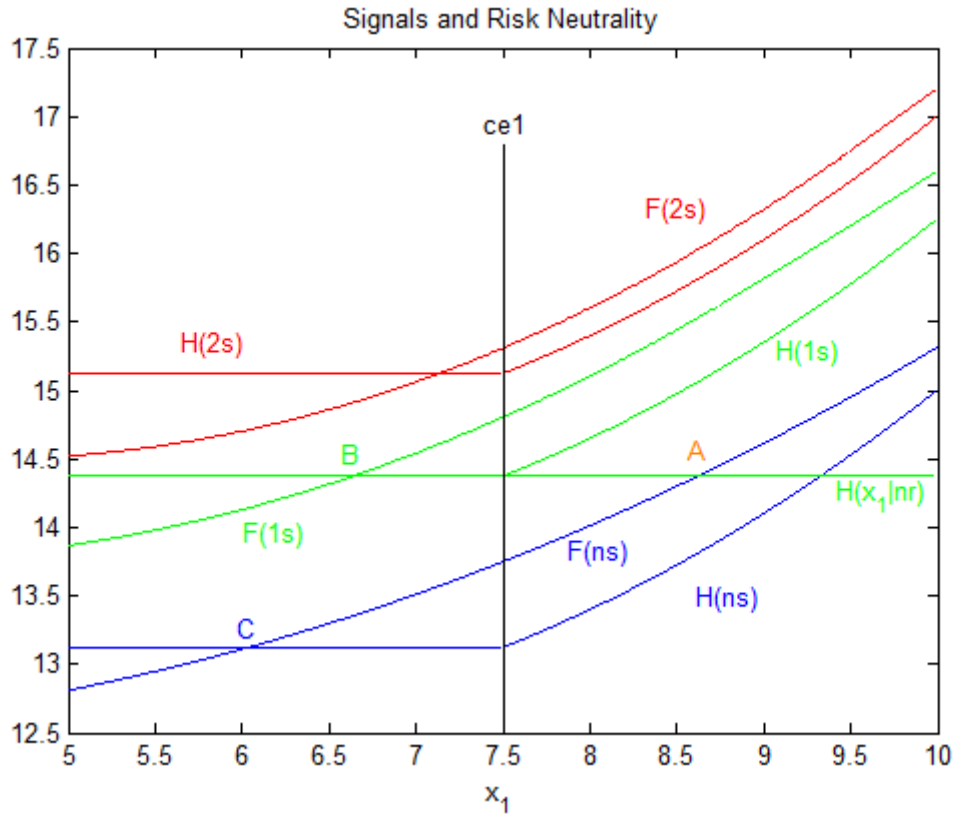


Refused certainty equivalent, signals and decision irreversibility:
threshold values and information gathering intervals
given risk averse utility functions and uniform risk distributions.

Note that the $H(\cdot)$ functions are both discontinuous. The vertical lines joining their respective sections have been included to simplify the comparisons made between the g.c.e.s. and the r.c.e.s.

Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$
Error! Bookmark not defined. Utility functions: $u_1(x_1) = x_1$; $u_2(x_2) = x_2$
 Probability densities: both continuous and uniform
 $\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}$; $\forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$

Figure 18



Evolution of the optimal threshold values given risk neutral utility functions and uniform risk distributions.

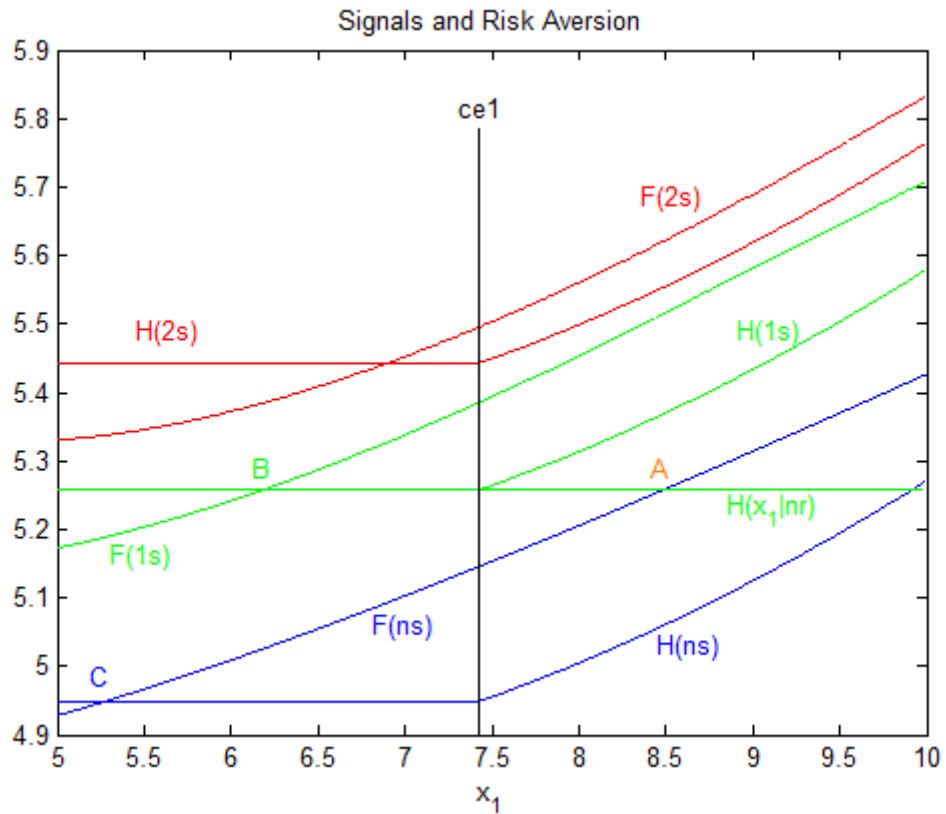
Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$

Error! Bookmark not defined. Utility functions: $u_1(x_1) = \sqrt{x_1}$; $u_2(x_2) = \sqrt{x_2}$

Probability densities: both continuous and uniform

$$\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}; \quad \forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$$

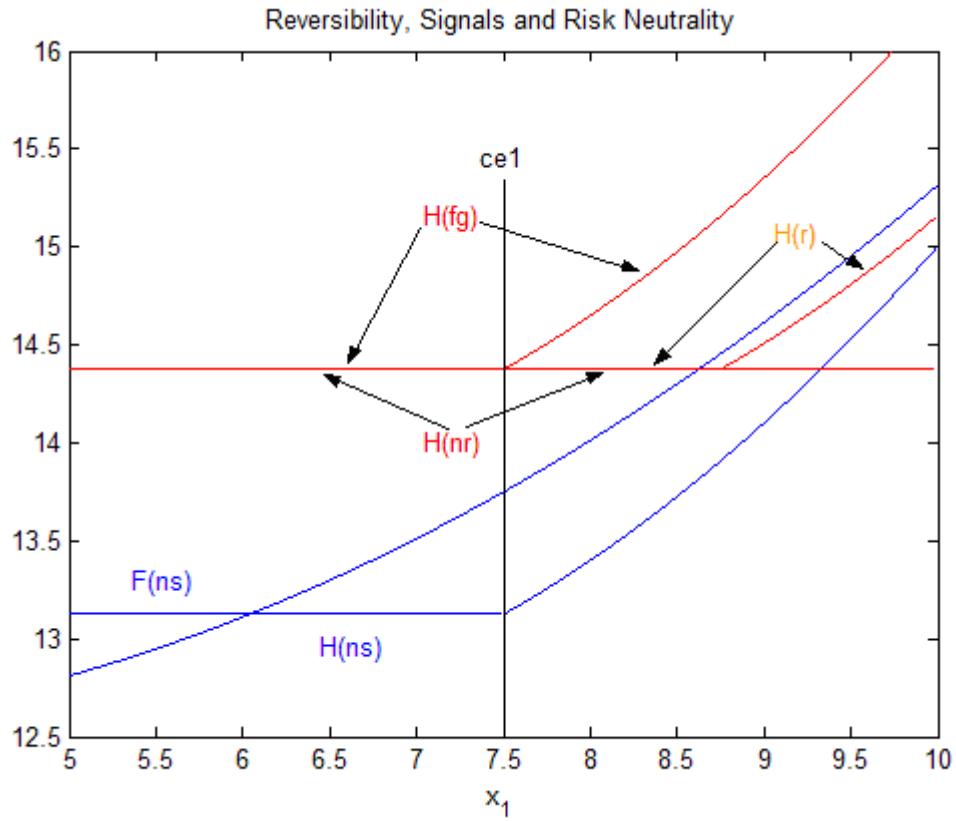
Figure 19



Evolution of the optimal threshold values given risk averse utility functions and uniform risk distributions.

Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$
Error! Bookmark not defined.Utility functions: $u_1(x_1) = x_1$; $u_2(x_2) = x_2$
 Probability densities: both continuous and uniform
 $\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}$; $\forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$

Figure 20



Market transition thresholds for the different types of decision processes given risk neutral utility functions and uniform risk distributions.

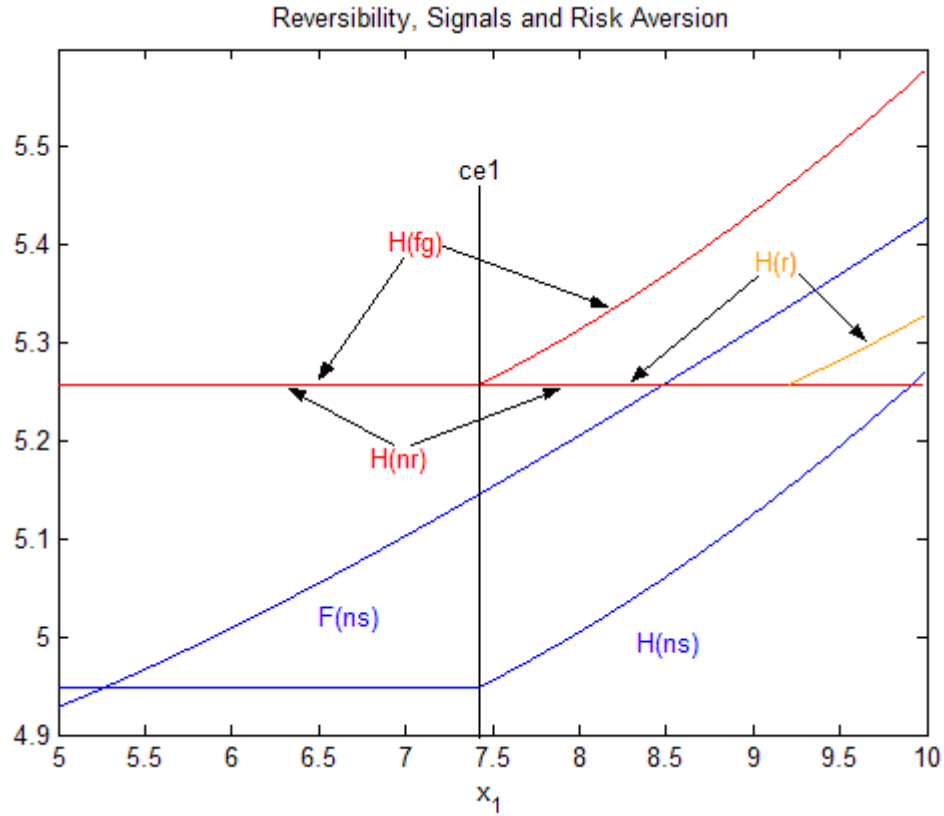
Characteristic spaces: $X_1 = [5,10]$, $X_2 = [0,10]$

Error! Bookmark not defined. Utility functions: $u_1(x_1) = \sqrt{x_1}$; $u_2(x_2) = \sqrt{x_2}$

Probability densities: both continuous and uniform

$$\forall x_1 \in X_1, \mu_1(x_1) = \frac{1}{5}; \quad \forall x_2 \in X_2, \mu_2(x_2) = \frac{1}{10}$$

Figure 21



Market transition thresholds for the different types of decision processes given risk averse utility functions and uniform risk distributions.

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Amplio resumen de la tesis:

Un modelo de cambio tecnológico en equilibrio general basado en la demanda

Resumen Principal

Esta tesis estudia como la capacidad de adquisición de información de los individuos afecta la tendencia de innovación tecnológica, estableciendo una conexión explícita entre la demanda de mercado, las empresas y la evolución de la dinámica tecnológica. Se examinan los efectos que diversas estructuras teóricas de demanda tienen en los incentivos de las empresas para señalar la existencia e introducir productos tecnológicamente superiores. Por ejemplo, se ilustra como, tras observar una señal creíble y positiva, las fricciones existentes en el mercado pueden retrasar la adopción de la ambas tecnologías, la actual y la recién introducida y superior. Las consecuencias derivadas de la existencia de fenómenos de dependencia acumulativa se analizan teniendo en cuenta explícitamente el proceso de difusión de información entre individuos y la generación de efectos de red que pueden tener lugar después de que las empresas señalen la disponibilidad de grupos de productos superiores tecnológicamente. También se ilustra como la generación de nichos tecnológicos de mercado depende de la habilidad de los individuos para revertir sus procesos de adquisición de información y comparar los productos observados en diversos mercados antes de tomar una decisión. Además, se obtienen situaciones de equilibrio donde la introducción de productos superiores tecnológicamente y la subsecuente creación de nichos de mercado es subóptima para la empresa que envía la señal correspondiente. Este resultado describe la idea central de la tesis, la cual, mediante la utilización de un marco teórico lo suficientemente cercano al de equilibrio general, permite generar conexiones con la perspectiva económica ortodoxa en materia de innovación tecnológica. Finalmente, se introducen simulaciones numéricas para ilustrar todos los resultados teóricos obtenidos.

Objetivos

La tesis actual tiene como objetivo principal la modelización del cambio técnico desde el punto de vista de la demanda. La literatura económica tiende a analizar el cambio técnico y la introducción de nuevos productos desde el punto de vista de la oferta, mientras que la demanda permanece aislada como un mero recipiente de innovaciones las cuales son siempre adquiridas tan pronto como son reconocidas. Este equilibrio parcial determinado por los movimientos en la oferta constituye un límite importante a la hora de analizar la introducción de nuevos productos y la generación de nichos de mercado, ambos fundamentales en la evolución de la oferta tecnológica. De hecho, la mayoría de las mejoras tecnológicas que tienen lugar últimamente en el mercado tienen a la demanda tecnológica como un factor fundamental en su desarrollo, como es por ejemplo el caso de

la demanda de Iphones. Por lo tanto, la integración de la demanda como parte del modelo de equilibrio general que determina la evolución de la tecnología en el mercado actual es fundamental y a la vez necesaria para entender el proceso de evolución tecnológica.

Metodología

La tesis actual desarrolla un modelo normativo de demanda racional que tiene en cuenta la incertidumbre implícita en el proceso de adquisición de información y elección de los individuos. Por lo tanto, un modelo matemático basado en los axiomas de expectativas racionales se desarrolla junto con la capacidad limitada de los individuos para asimilar información. Como todo modelo de equilibrio general,, el lado de la demanda es complementado por el de la oferta cuando este ultimo tiene en cuenta la generación de expectativas y elecciones de los individuos al decidir si introducir o no un nuevo producto tecnológico en el mercado. La simulación numérica de todos y cada uno de los resultados basados en un amplio espectro de posibilidades constituyen el apoyo y la intuición requeridas para desarrollar el modelo.

Resultados

Los resultados obtenidos indican un comportamiento hasta ahora no identificado en la elección racional de los individuos cuando se les presenta con mejoras tecnológicas en los productos disponibles. En concreto, la tesis actual ilustra como los individuos pueden ser racionalmente reticentes a asimilar y adquirir nuevas tecnologías aunque estén convencidos de su valor como innovaciones tecnológicas. Cuando se consideran simultáneamente el lado de la oferta y la demanda el modelo desarrollado en esta tesis concluye que las empresas pueden ser reticentes a la introducción de mejoras tecnológicas en sus productos debido a dichas fricciones, un fenómeno que no ha sido reconocido por la literatura económica a pesar de preguntarse continuamente por la tardanza en la difusión de innovaciones tecnológicas entre agentes racionales dentro del mercado. Otros resultados emergen dentro del modelo actual que indican el camino para futuros desarrollos basados en la demanda dentro de modelos de equilibrio general.

Extensiones

La extensión mas evidente consiste en desarrollar la capacidad de adquisición de información y asimilación de los individuos y ver como afecta a la introducción de productos cada vez mas complejos tecnológicamente y a los mercados de búsqueda como Internet. Desarrollando las capacidades de asimilación de los individuos de forma diversa en cada situación, el modelo actual permite desarrollar nuevos equilibrios y analizar diversas situaciones de asimilación de información que permanecen ocultas y no estudiadas dentro del contexto actual de la teoría económica.

Large summary of the Ph.D. Thesis:

A general equilibrium demand-based approach to technological change

Main Summary

This thesis analyzes how the information acquisition capabilities of decision makers affect the patterns of technological innovation, establishing a explicit link among market demand, firms and the evolution of technology dynamics. We examine the effects that different decision theoretical driven demand structures may have on the incentives of firms to signal the existence of and introduce technologically superior products. For example, we illustrate how, after the observation of a positive credible signal, market frictions may cause a slow-down in the adoption of both the currently available technology and the newly introduced superior one. The consequences derived from the existence of path dependence phenomena will be analyzed by explicitly accounting for the process of information diffusion among decision makers and the emergence of bandwagon and network effects that may take place after firms signal the availability of a technologically superior set of goods. We also illustrate how the generation of technological niche markets depends on the ability of decision makers to reverse their information gathering processes and compare the goods observed in different markets before making a choice. In addition, we obtain equilibrium situations where the introduction of technologically superior products and subsequent generation of niche markets is suboptimal for the signaling firm. This result embodies the main idea of the thesis, which, by using an environment sufficiently close to the general equilibrium framework, allows for bridges to be built with the economic orthodox perspective on technological innovation. Further, numerical simulations are introduced to illustrate all the theoretical results obtained.

Objectives

The current thesis has as a main objective the modelization of technological change from the demand point of view. The economic literature tends to analyze technological change and the introduction of new products from the point of view of the supply, while the demand remains isolated as a mere recipient of innovations that are always acquired as long as they are recognized by decision makers. This partial equilibrium determined by movements in the supply side constitutes an important constraint when analyzing the introduction of new products and the generation of niche markets, both of which are fundamental in the evolution of technological supply. Indeed, most of the current technological improvements taking place in the market have the technological demand as a fundamental factor in their development, i.e. the demand for iPhones. As a result, the integration of demand as an active part of the general equilibrium model determining

the evolution of market technology in the current state of the world is fundamental and essential to understand the process of technological evolution.

Methodology

The current thesis develops a normative model of rational demand that accounts for the implicit uncertainty in the information acquisition and choice processes of decision makers. As a result, a mathematical model based on the axioms of rational expectations is developed together with the limited ability of decision makers to acquire and assimilate information. Like any other general equilibrium model, the demand side is complemented by the supply side when the latter one accounts for the generation of expectations and choices made by decision makers when deciding whether or not to introduce a new technological product in the market. The numerical simulation of each and every one of the results based on a wide spectrum of possibilities constitute the support and intuition required to develop the model.

Results

The results obtained indicate a behavior that has remained unidentified until now in the rational choices made by decision makers when presented with technological improvements in the products available. In particular, the current thesis illustrates how decision makers may be rationally reticent to assimilate and acquire new technologies despite being convinced about their worthiness as technological innovations. When the supply and demand sides are considered simultaneously, the model developed in the current thesis concludes that firms may be reticent to introduce technological improvements in their products due to the aforementioned frictions, a phenomenon that has not been recognized in the economic literature despite the fact that it constantly wonders about the delays in the diffusion of technological innovations among rational agents within a given market. Other results arise from the current model that open the way for future developments based in the demand within a general equilibrium environment.

Extensions

The most evident extension consists of developing the information acquisition and assimilation capacities of decision makers in order to see how they affect the introduction of products that become technologically more complex within search markets such as the internet. By developing the capacities of decision makers in different ways based on each particular situation, the current model allows for the generation of new equilibria and the analysis of different information assimilation situations that remain hidden in the current economic theoretical context.